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Diffusion and Management of Disruptive Technology in Cities: The Case of Drones

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Diffusion and Management of Disruptive Technology in Cities: The Case of Drones

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Urban Planning and Public Policy

by

Xiangyu Li

Dissertation Committee:
Associate Professor Douglas Houston, Co-Chair
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Professor Scott A. Bollens

2022

DEDICATION

To

an intellectually brave (stubborn) man who chose to study drones in
an urban planning dissertation: me

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Journal Articles

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Kim, J.H., and **Li, X.** (2018) Transportation Plans: Their Informational Content and Use Patterns in Southern California. *Association of Collegiate Schools of Planning*, Buffalo, NY, Oct. 26-28

Kim, J.H., and **Li, X.** (2019) Understanding the dynamics of urban densification:

How do current and planned land uses interact and evolve over time? *Annual Meeting of the North American Regional Science Council*, Pittsburgh, PA, Nov. 13-25.

Li, X., and Kim, J.H. (2020) Managing Technology-driven Challenges: Exploring the Patterns of Local Drone Policy Adoption in California. *Association of Collegiate Schools of Planning*, Toronto, Canada, Nov. 5-8 (Online).

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ABSTRACT OF THE DISSERTATION

Diffusion and Management of Disruptive Technology in Cities: The Case of Drones

by

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Doctor of Philosophy in Urban Planning and Public Policy

University of California, Irvine, 2022

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While the industry of civilian unmanned aerial vehicles (UAV) or drones has seen rapid expansion in the past decade, few studies have systematically examined the dynamics between this disruptive technology and various aspects of cities. Employing quantitative methods, this dissertation explores 1) the diffusion and adoption patterns of civilian drones; 2) how cities manage the challenges of increasing drone activities; and 3) the supply-side opportunities and constraints associated with the deployment of Urban Air Mobility (UAM) in built-out metropolitan areas. The results of the first county level study might suggest (Chapter 2) that the digital divide has magnified the uneven and nonlinear diffusion of drones across time and space. Furthermore, the strength of state-level interventions correlates with the intensity of local drone adoption, even though the regulatory effects are different among drone user groups. People living in neighborhoods with a higher adoption rate of drones are on average younger, more affluent, and Whiter. An extension of the first study at the zip code level (Chapter 3) has retested the key results and provided additional insights into the spatial dependence effects that affect the drone

adoption patterns. Furthermore, the results of the second study (Chapter 4) indicate that local drone policy adoption among communities of color trails behind that of other communities. Although drone policy adoption at the local level has been shaped by both motivation and capacity factors, the desire to protect public facilities appears to motivate localities to adopt regulatory measures. In particular, policy adoption is influenced by what nearby cities do, suggesting that strategic interaction is at play among local governments. In the third study (Chapter 5), I evaluate the supply-side opportunities and constraints associated with UAM adoption through a systematic scenario analysis. The results of the third study indicate that current supply-side infrastructure opportunities in Southern California, like helipads and elevated parking structures, are widely available to accommodate the regional deployment of UAM service although current spatial constraints can significantly limit the location choice of UAM landing sites (vertiports) for electric vertical take-off and landing (eVTOL) aircraft. Moreover, the low-income and young populations tend to live relatively farther away from the supply-side opportunities compared to the general population. The third study also proposes a network of UAM stations in Southern California based on the joint considerations of available infrastructure and home-workplace commuting flows.

INTRODUCTION

Emerging technologies are defined by their novelty, rapid growth, prominent impact, and uncertainty (Rotolo et al., 2015). Over the past decade, there has been a proliferation of civilian unmanned aerial systems, more popularly known as drones. In the United States, the number of total drone registrations more than quintupled from 300,000 to over 1.5 million between 2016 and 2020 (FAA, 2020). Although recreational drones comprise a large portion of the total registrations, commercial drones have also seen a rapid increase. Apart from the professional applications of drones in surveillance, filming, and agriculture, drone technologies hold great promise in planning. For instance, they are quickly becoming indispensable tools to collect “high-quality, accurate, and timely data to analyze sites and make data-driven decisions” (Stephens et al., 2020, p. 5). Drone data have been used for mapping, 3D modeling, and design to support a range of planning activities, including transportation, environment, and disaster planning.

However, as drones are straddling both public and private space with their capacity to be remotely controlled and record images and videos, there have been increasing public concerns over safety, privacy, and potential weaponization of drones (Clothier et al., 2015; Nelson et al., 2019; West et al., 2018). Although all levels of government have implemented regulations on drones, localities are at the center of drone management given the decentralized nature of drone activities and their operational characteristics (e.g., short-range, low-altitude, within visual line of sight). The exponential growth of drones and the increasing challenges to manage drones in both public and private space necessitate studies on how drones are diffused and distributed across time and space and how cities are responding to this emerging technology. Without such understanding, it is difficult to develop targeted and appropriate public policies to protect the public interest while nurturing the continuous development of the drone industry.

Another notable trend of drone technology, given its rapid evolvement, is the materialization of Urban Air Mobility (UAM). Owing to the rapid technological advances in electric vertical takeoff and landing (eVTOL) vehicle technology, the UAM system has reached "a level of maturity to enable UAM using safe, quiet, and efficient unmanned vehicles to conduct on-demand and scheduled operations [for human transport] (Thipphavong et al, 2018, p.1)." Before taking off, eVTOL vehicles first need places to land. Although current studies on UAM explores both hub-to-hub (like rail and air transport) and door-to-door (like Uber) scenarios, the maintenance requirements of aircraft are likely to diminish the possibility of a door-to-door UAM system at the early stage of adoption. Therefore, it is important to identify the location of UAM landing sites that capture the potential travel demand while considering supply-side constraints and opportunities.

To untangle these complex but interrelated issues on drones, this dissertation employs an analytical framework to guide the analyses (Figure 1.1). More details are described below.

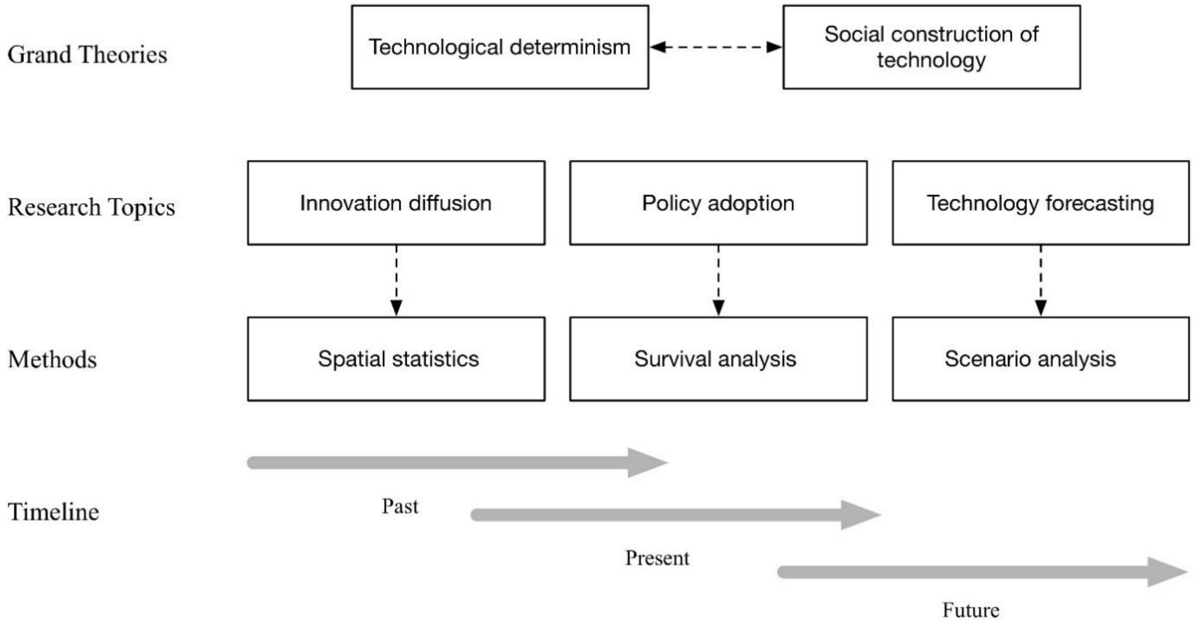

Figure 1.1 Analytical Framework of the Dissertation

I pose the following three interrelated questions to delve deeper into civilian drone technologies and their implications for current and future planning research and practice.

1) How have civilian drones diffused across time and space in communities?
2) How have localities managed the proliferation of drone activities?
3) What are the supply-side opportunities and constraints associated with the future deployment of UAM in built-out metropolitan areas?

To address the above questions this dissertation is organized as follows.

Chapter 1 reviews literature to explore how the concept of socio-tech interaction has evolved from an emphasis on technological determinism to a dynamic and iterative process involving a diverse range of factors other than just technology.

Chapter 2 investigates the first research question on the diffusion patterns of drones at various geographical scales. Then this county-level study explores the spatial temporal patterns of the adoption of drones across the U.S. The results suggest that the adoption rate of digital infrastructure, like broadband technology, is positively associated with the magnitude and pervasiveness of drone adoption. Furthermore, results of the study indicate that the strength of state-level interventions is associated with the intensity of local drone adoption, even though the regulatory effects may be different among drone user groups (recreational vs. commercial). The results paint a demographic picture of the people living in neighborhoods with a higher adoption rate of drones, who are on average relatively younger, more affluent, and Whiter.

Chapter 3 is an extension of Chapter 2 with a focus on zip-code level analysis, which explores the drone adoption patterns from 2015 to 2019 in Southern California. The study focuses on the relationship between the drone adoption rate and high-speed broadband coverage. The results reveal that the drone adoption rate was geographically uneven and affected by the spatial dependence effect, and drone adoption hotspots appeared to be clustered in coastal areas. Meanwhile, areas with higher early drone adoption tended to have relatively more economically well-off young adults, while the drone adoption rates of Black and Hispanic communities lagged. The findings suggest the need for the development of policy interventions to reduce information inequality in the adoption of innovations.

Chapter 4 explores the research question of how localities respond to and manage the proliferation of drone activities through local policies. This study examines the dynamics of local drone policy adoption, focusing on California, which has the largest population of drones currently registered in the United States. A review of 482 California cities' municipal codes shows evolving patterns of policy adoption over the last two decades, with a rapid expansion since 2015. The multivariate survival analysis indicates that policy adoption at the local level is shaped by both municipal capacity and motivation factors, including the actions of neighboring cities. The analysis also finds evidence of disparities associated with socio-demographics, calling for more attention to the variation in local policy responsiveness to technology-driven challenges and ways to support local efforts and their collaboration.

Chapter 5 provides an initial assessment of the supply-side opportunities of UAM in Southern California with a scenario analysis that examines spatial constraints such as noise levels, school buffer zones, and airspace zones into consideration. The corresponding travel demand that can be potentially captured under each scenario was estimated with the home-workplace trip table. The results of the analyses indicated that current supply-side infrastructure opportunities, like helipads and elevated parking structures, are widely available to accommodate the regional deployment of UAM service although current spatial constraints can significantly limit the scope of vertiport location choices. Furthermore, the low-income population and young people tend to live farther away from the supply-side opportunities compared to the general population. Moreover, the study proposes a network of UAM stations based on the joint considerations of available infrastructure and home-workplace commuting flows.

Chapter 6 is the conclusion of the dissertation. The chapter revisits the major findings, contributions, and limitations of the dissertation. Several future research directions to improve the research agenda on disruptive technology are briefly discussed.

Chapter 1. A literature review of the grand theories of society and technology

Scholars from various fields have studied the diffusion patterns of technology and its interactions with organizations for nearly a century. In recent years, there have been increasing interdisciplinary interests in the nexus between innovation diffusion studies and urban studies as the disruptions of emerging technologies have gone beyond specific business sectors to impact various areas of public life. This trend has ignited broad interest in understanding how technologies interact with urban systems, particularly in ways that focus on managing the uncertainties of disruptive technologies. In this chapter, I provide a review of the grand and middle-range theories of technology-society interactions. More detailed empirical lessons from innovation diffusion studies, policy adoption studies, and recent advancements in urban air mobility technology are presented in the following chapters.

1.1 Theories of technology-society interactions

Theories of technology-society interactions attempt to explain the factors related to technological advancement and the impact of technology on society. While early theories like Technological Determinism and Social Construction of Technology emphasize the unidirectional causation between technological disruptions and social forces, contemporary theories of technology challenge these views by arguing that technology and social structure are mutually and recursively influence each other in complex ways.

1.1.1 Technological Determinism (TD) and Social Constructivism (ST)

Technology refers to technological systems such as the internet, as well as artifacts, rules, and beliefs that make up these systems, such as mobile phones, protocols, and consensus about the credibility of the online information (Dafoe, 2015). This broad definition of technology has made the debate on tech-social interactions more complicated. Two classic contradictory views are Technological Determinism (TD) and Social Constructivism (SC). TD is a theory that sees the effects of technology as being the major determinant of cultural and social change, which held that the nature of technologies and the direction of tech-driven change were predetermined (perhaps subject to an inner 'technical logic' or 'economic imperative'), and technology had determinate impacts upon work, economic life, and society (Ellul, 1964). This radical deterministic view emphasizes the autonomy of technological change and the unidirectional impact of technology on society. One of the earliest examples of TD is the "Great Stirrup Controversy." White (1962) argued that it is the invention of the stirrup made mounted shock combat possible. This new level of lethality was seized by the Franks (ancient Germanic tribes) in the eighth century. The warrior training techniques and the resources necessary to sustain them had decisively transformed society from slavery to feudalism. White's (1962) book Medieval Technology and Social Change has proved very influential, but others have accused him of oversimplification and ignoring contradictory evidence on the subject. Two other pro-determinism ideas are Technological Momentum (Hughes, 1983) and Technological Frames (Bijker, 1995). These ideas are signs of transition from radical TD to more inclusive and dynamic views of technology. Technological Momentum frames that as technological systems mature and sunk costs increase, they are more likely to further constrain social systems, even though at the early stage the relationship between technology and society is reciprocal (Hughes, 1983). Similarly, Bijker (1995) believes that the practices, shared meanings, and infrastructure produced by adopting technology are inevitable frames that constrain the freedom of social forces to reproduce new technologies.

In contrast to TD, the social shaping perspective, or the social constructivism (SC), emerged from the critique of technological determinism, which investigates how social, institutional, economic, and cultural factors have shaped: (1) the direction as well as the rate of innovation; (2) the form of technology: the content of technological artifacts and practices; and (3) the outcomes of technological change for different groups in society (Bijker, 1995; Williams,1996). SC signals sociology's rediscovery of technology by focusing on the seamless web of interaction between social forces and technology and the social process that create objective reality (Bijker, 2010; Hughes, 1983). One of the examples of SC is Bijker's (1995) analysis of the evolution of the design of bicycles. This non-linear progression towards the most efficient and practical bicycle we have today necessitates the role of social groups in technology adoption. Bijker (1995) broke down the social construction of bicycle based on how it is seen by manufacturers, non-users, and users of different kinds. He analyzed these differences by asking each group their perceptions of the bicycle. Non-users describe the machine as being dangerous. Similarly, users observe the risky element of the bicycle, however, find this aspect of adventure appealing and is what draws them towards the use of bicycles. The "interpretative flexibility" inherent within SC stands for a group-dependent lens of analysis. Bijker also touches specifically on the example of the air tire and how the advancement of this element was viewed by various users—the racers were concerned about speed; others appreciated its convenience and stability while producers were focused on economic outcomes. "Relevant social groups do not simply see the same aspect of one artifact. The meaning given by a relevant social group constitutes the artifact" (Bijker, 1995, p.77). As a result of these heterogeneous interpretations, there had existed many designs of bikes (e.g., velocipedes, bicycles, and tricycles). Some had two wheels others had three, some had different size wheels others the same size, some had solid tires some pneumatic ones. By 1897 the bicycle as we know it, air tires, two wheels of the same size, chain-driven on the rear wheel was in existence. After a SC process lasting several decades, the interpretive flexibility of the technology had been erased. From the lens of SCOT, the final formation of bicycles today is not a predetermined outcome by the technology, but a recursive process driven by social forces. In summary, departing from technological determinism, SC looks at the predominant ways in which social groups construct technological reality. However, SC has drawn a lot of critiques from sociologists. Winner (1993) identifies the following limitations in social constructivism: (1) It explains how technologies arise, but ignores the consequences of the technologies after the fact; (2) It examines social groups and interests that contribute to the construction of technology, but ignores those who have no voice in the process, yet are affected by it; (3) It is superficial in that it focuses on how the immediate needs, interests, problems and solutions of chosen social groups influence technological choice, but disregards any possible deeper cultural, intellectual or economic origins of social choices concerning technology.

Two other theoretical perspectives that adopt a systematic and dynamic perspective of technology are noteworthy because they bring more theoretical lenses to study the interactions between technology and society rather than debating which one has more power to shape the other.

1.1.2 Actor-Network Theory (ANT) and Structuration Theory (ST)

Positioning in the middle of the debate between constructivist and determinists studies, ANT emphasizes a systemic and dynamic perspective toward the study of techno-social systems (Bloomfield and Vurdubakis, 1997). The theory equally defines human or non-human actors as agents that influence the techno-social system (Latour, 1992). This approach places the focus of ANT analysis on the dynamic interactions among agents as actors acquire their attributes because of their relations with other actors (Law, 1992). According to Latour (1992), there are five key elements of ANT:

- Actors are all "entities that do things". Actors can be human and non-human, with no distinction being made between them.
- A black box is a collection of entities (can be actors or networks or both) that is considered stable and the details of which need no longer be considered.
- A network is a group of unspecified relationships between entities (actors). Actors and networks are mutually constitutive.
- Properties of a setting that make certain things possible and others impossible are called prescriptions.
- An intermediary is the link that connects actors to networks and defines the network itself. Actors circulate intermediaries between themselves to form networks.

For example, rather than saying Elon Musk created Tesla, Actor-Network theorists would consider all surrounding factors — no one acts alone. Elon's past experiences, his colleagues, his deep connections with venture capital, support from governments, the recall of General Motors electric cars in 2003, and various other technical and non-technical elements would all be described and considered in his actor-network. Network Theory does not typically attempt to explain why a network exists; it is more interested in the infrastructure of actor-networks, how they are formed, how they interact with one another, etc. It is noted that, even though ANT has gained a lot of popularity and provided a different lens to investigate the dynamics between society and technology, there are various criticisms held regarding ANT. For instance, no accommodations for power imbalances among actors can be made because it assumes all actors are equal within the network.

Another theory that departs from determinism and constructivism is the structuration theory. To speak of structure, Giddens (1984) defines it as rules and resources—the former implies the 'methodical procedures' of social interactions while the latter could be authoritative or allocative, internal or external (Feldman, 2004; Orlikowski, 1992;). The theory employs a recursive notion of actions constrained by structures that are produced and reproduced by actions. Sewell (1992) argues that structure is a dynamic cultural phenomenon; it is multifaceted, ambiguous, and overlaps one another. The theory also recognizes the mutually sustaining relationship between rules and resources. For instance, the house is given its shape by the application of schemas (e.g., zoning and design guidelines), and the house in turn inculcates these schemas by allocating resources to differently coded spaces (Sewell, 1992). From the perspective of structuration theory, technology is examined as a proxy through which people interact with structures that shape and reshape the use of technology. By drawing upon the structuration theory, Orlikowski (1992) has applied the duality of structure to conceptualizing technology as structure in organizations. The structuration model proposed by the author unveils the dual nature of technology as both objective realities and as socially constructed products.

1.2 Diffusion and adoption of innovations

The theory of innovation diffusion (Rogers, 2003) is a popular framework to study the adoption of technology or broadly defined disruptive powers (e.g., policies, ideas, rumors, etc.) in a variety of fields. The diffusion process is conceptualized as information of innovation shared among social groups through communication channels over a certain period. At the individual level, users of the innovation experience four major steps towards the final adoption of innovation: persuasion, decision, implementation, and confirmation. Several internal characteristics (e.g., innovation characteristics) and external contexts (e.g., communication channels) would influence the innovation adoption process. The following section delves into a review of the innovation diffusion theory and empirical factors related to the adoption of innovations.

1.2.1 Diffusion of innovation theory

If the Technological Determinism, Social Constructivism, and Structuration Theory are grand philosophical ideas in the field of social-tech study, the Diffusion of Innovation Theory (DIT) is a middle-range theory that has been broadly implemented in marketing, public health, communication, sociology, and geography. “Diffusion [of innovation] is the process in which an innovation is communicated through certain channels over time among the members of a social system (Rogers, 2003, p.5).” From the spatial dimension, Innovation diffusion theory suggests that (Grübler, 1996, p.29): (1) No innovation spreads instantaneously. Instead, a typical S-shaped temporal pattern seems to be the rule. This basic pattern appears invariant, although the regularity and timing of diffusion processes vary greatly; (2) Diffusion is a spatial as well as a temporal phenomenon. Originating from innovation centers, a particular idea, practice, or artifact spreads out to its hinterland by means of a hierarchy of sub-innovation centers and into the periphery, defined spatially, functionally, or socially; (3) The periphery, while starting adoption later, profits from learning and the experience gained in the core area and generally has faster adoption rates. As the development time is shorter, however, the absolute adoption intensity is lower than in innovation centers or in core areas (spatial or functional) proximate to them (explained more in detail in the Geography of Innovation); (4) Although diffusion is essentially a process of imitation and homogenization, it clusters and lumps; (5) Technology diffuses slower to locations that are farther away from adoption leaders. This effect is generally stronger across high-income/GDP areas.

To take a closer look into the mechanism of innovation diffusion, Roger (2003) introduced a four-element framework to investigate the diffusion process beyond physical space and time. The four elements are:

- Innovation
- Communication channels
- Time span
- Social system

Each basic element has its characteristics. An innovation could be an idea, practice, or object that is perceived as new by an individual or other unit of adoption. Among the diffusion scholars, important questions regarding various innovations are: (1) how earlier adopters differ from later adopters of an innovation; (2) how the perceived attributes of innovation, such as relative advantage, compatibility, and so on, affect its rate of adoption; and (3) why the S-shaped diffusion curve "takes off" at about 20-30 percent adoption, when interpersonal networks become activated, that a critical mass of adopters begin to use an innovation. Innovation could be either good or harmful to a different group of adopters. There are several key factors (or groups of metrics), including relative advantage, compatibility, complexity, trialability, and observability can be used to measure the adoption characteristics of innovations. Relative advantage is the degree to which an innovation is perceived as better than the idea it supersedes, which can be measured in economic terms, social prestige factors, convenience, satisfaction, etc. The key hypothesis is the greater the perceived relative advantage of an innovation, the more rapid its rate of adoption will be. Compatibility is the degree to which an innovation is perceived as being consistent with the existing values, past experiences, and needs of potential adopters. Compatibility would also hypothetically have a positive correlation with the adoption rate. Complexity is the degree to which an innovation is perceived as difficult to understand or use, which should be inversely related to the adoption rate. Trialability is the degree to which an innovation may be experimented with on a limited basis. New ideas that can be tried on the installment plan will generally be adopted more quickly than innovations that are divisible. For instance, Ryan and Gross (1943) found that Iowa farmers adopt hybrid seed corn by first trying it on a partial basis. A trialable innovation would have less uncertainty for a individual who is considering it for adoption. Observability is the degree to which the results of an innovation are visible to others. The easier it is for individuals to see the results of an innovation, the more likely they are to adopt it. Theoretically, past research indicates that innovations that are perceived by individuals as having the greater relative advantage, compatibility, trialability, observability, and less complexity will be adopted more rapidly than other innovations.

Second, the communication channel is the process by which participants create and share information to reach a mutual understanding (Rogers, 2003). Mass media/virtual network channels are usually the most rapid and efficient means of informing an audience of potential adopters about the existence of innovation. Additionally, interpersonal channels, involving a face-to-face exchange of information between two or more individuals, have become important channels fueling innovation diffusion. To be noted that, one of the most important problems in the diffusion of innovations is that the participants are usually quite homogenous. Homophily is the degree to which two or more individuals who interact are similar in certain attributes (education, socioeconomic status, etc.). "In a free-choice situation, when an individual can interact with any one of a number of other individuals, the tendency is to select someone similar (Rogers, 2003, p.19)."

Third, time is the third element of the innovation diffusion process (Rogers, 2003). The time dimension has three metrics to be measured: (1) The innovation decision process; (2) the innovativeness and adopter categories; and (3) the rate of adoption. Specifically, the innovation decision process includes five steps:

- Knowledge
- Persuasion
- Decision
- Implementation

- Confirmation

Innovativeness is the degree to which an individual or other unit of adoption is relatively earlier in adopting new ideas than the other members of a system. In this sense, we may classify innovation adopters into five groups: innovators, early adopters, early majority, late majority, and laggards. The rate of adoption is the third way to measure the time dimension of innovation diffusion. The theoretical diffusion rate pattern as suggested by Rogers (2003), is an S-shaped curve. One issue addressed by diffusion research is why some innovations have a rapid rate of adoption, while others are adopted more slowly.

The fourth element is a social system, which is defined as "a set of interrelated units that are engaged in joint problem solving to accomplish a common goal (Rogers, 2003, p. 23)." The members or units of a social system may be individuals, informed groups, organizations, and/or subsystems. When innovations diffuse through a social system, the social structure of the system affects the innovation's diffusion in several ways. More in-depth knowledge could be found in social network theory. Just like every herd of wild cattle has its leaders, opinion leaders are important in determining the rate of adoption of an innovation in a network. In general, there are two types of models in communication, 1) the Hypodermic Needle Model (HNM), and 2) the two-step flow model. The first model suggests that the mass media had direct, immediate, and powerful effects on a mass audience. But critics argue that the HNM is too mechanistic, and too gross to give an accurate account of media effect. It ignored the role of opinion leaders. The Two-Step Model (TSM) suggests that "ideas often flow from information source to opinion leaders and from these to the less active selection of population" (Lazarsfeld et., 1994, p. 151). The TSM indicates that communication messages flow from a source, via mass media channels, to opinion leaders. Then the information is further disseminated to followers. Additionally, the diffusion network is enhanced by the concepts of homophily and heterophily. The analysis of communication networks is a method of research for identifying the communication structure in a system, in which network data about communication flows are analyzed by using interpersonal relationships. Specifically, two related theories are very popular in this branch of study. The Strength-of-Weak-Ties Theory (Granovetter, 1973), and the Social-Leaning Theory (Bandura, 1977). Other critical definitions in the diffusion network include:

- The critical mass: a point at which enough individuals in a system have adopted an innovation so that the innovation's further rate of adoption becomes self-sustaining.
- The threshold is the number of other individuals who must be engaged in an activity before a given individual will join that activity.
- Communication proximity is the degree to which two linked individuals in a network have personal communication networks that overlap.

The diffusion of innovation is a complex phenomenon. The complexity arises from the multifaceted nature of the interaction between the technology and the dynamic context in which it is embedded. For instance, the human-computer interaction (HCI) tradition underwent some fundamental changes during the last decade (e.g. wearable technology, AR/VR, smart home gadgets, etc.). Originally focusing on computer engineering and human information processing, increasing emphasis has been put on the influence of culture, emotions, and experience on technology design and development (Hassenzahl & Tractinsky, 2006). These fundamental changes suggest that the diffusion and adoption of technology are part of a more dynamic process and that they are context dependent. No single theoretical perspective provides a full understanding of the phenomenon, but Roger's theory remains a popular starting point for many works among different schools of literature. Following Roger's theory, a range of publications, mostly at the level of organization, have provided evidence on factors related to decisions to adopt innovations and how the likelihood of adoption of innovations can be increased. *Physical context* is associated with adoption. For instance, urbanization and development around an adopting organization have a positive association (Damanpour & Schneider 2006; Meyer & Goes, 1988). *Policy and regulation* are positively associated with adoption, including specific enactment of policies, legislation, or regulations on innovation adoption(Aarons et al. 2011; Oldenburg and Glanz 2008; Rogers, 2003). Similarly, during the adoption phase, legislation accreditation standards are associated with increased user adoption (Aarons et al. 2011; Berta et al. 2005; Feldstein and Glasgow 2008). *Social networks and linkages* between systems outside an organization are positively associated with adoption (Oldenburg & Glanz 2008; Rogers 2003; Valente 1996). *Innovations* that are easy to use, better than current practice, observable, triable, cost-effective, compatible with user's norms and values, relevant, and low risk are more likely to be adopted (Rogers, 2003). Moreover, social climate and social influence, training readiness, cost-efficacy and feasibility, and other factors have been identified to have impacts on technology adoption. Table 1.1 provides a summary of various theoretical claims on factors associated with technology adoption.

Table 1.1 Factors associated with technology adoption for different research objects

Research objects	**Factors**
External system	External environment
	Government policy and regulation
	Inter-system social network
Organization	Absorptive capacity
	Network with innovation developers
	Norms, values, and cultures
	Size and structure
	Training readiness
Innovation	Complexity, relative advantage, and observability
	Cost-efficacy and feasibility
	Risks and benefits
	Triability, relevance, and ease of use
Individual	Attitudes, motivations, and readiness
	Individual characteristics
	Personal social network

Chapter 2. Diffusion Patterns of Civilian Drones in the United States

2.1 Introduction

Over the past decade, unmanned aerial vehicles (UAVs), more widely known as drones, have rapidly found their way back into civilian life from military battle zones (Jensen, 2016), as drone technology has become smaller and more affordable. The size and cost of components like gyroscopes, flight controllers, and cameras have dropped, and model aircraft equipped with high-definition video cameras capable of semi-autonomous and autonomous flight have become cheaper to buy or build—and ready-to-fly with little training. As of February 2020, more than 1.5 million drones, most of them owned by hobbyists, were registered with the Federal Aviation Administration (FAA, 2020). Besides the burgeoning market for recreational drones, the growing demand for the manifold of commercial or public drone applications in surveillance, inspection, mapping, and emergency response has also fueled the proliferation of civilian drones (Klauser & Pedrozo, 2015; Goodchild & Toy, 2018).

As the quantity and usage of civilian drones grow, so do safety, security, and privacy concerns over drone operations, especially in densely populated urban areas (Gallacher, 2016). In response to the emerging challenges and public concerns brought about by the proliferation of civilian drones, federal, state, and local governments have been increasingly enacting their own rules and guidelines for unmanned aircraft use. In September 2015, the FAA updated Advisory Circular 91-57 with stricter guidelines to pursue enforcement actions against persons operating model aircraft who endanger the safety of the National Airspace System (FAA, 2015). To fly a drone as a commercial pilot in the United States, drone pilots are required to follow the requirements of the FAA's Part 107 Small UAS Rules. To date, 24 states have passed legislation that falls within the broad category of privacy, 10 states have restricted drone access near critical facilities and infrastructure, and 19 states have assembled committees or advisory boards on drone regulation (NCSL, 2020).

However, the proliferation and regulation of the civil use of unmanned aircraft systems (UAS) throughout the United States have outpaced the study of the spatial/societal impact and mechanisms of drone diffusion (Joslin, 2015). In the existing literature, drone proliferation and its impact on urban space have been analyzed primarily from a conceptual or theoretical perspective. Insufficient evidence has been provided to inform empirical studies or policymaking. To address this issue, this paper explores a nationwide investigation of how drone technologies have been diffused across the United States from 2016 to 2019 using drone registration data published by the FAA. In light of the innovation diffusion theory, this study focuses on how digital infrastructure and various state-level regulatory elements shape the adoption process of drones. Moreover, the study paints a picture of the demographics of drone adopters. It is important to note that the "small T, large N" dependent variable (drone registrations), meaning few periods and many observations, is a major challenge in constructing a full panel dataset with the available socioeconomic datasets and choosing an appropriate estimation approach for the proposed statistical model. Thus, our baseline estimates only focus on the accumulated registrations over a four-year period with ordinary least squares (OLS) regression.

The results suggest that digital infrastructure, measured in terms of the broadband network subscription rate, is positively associated with the adoption of drones. The strength of state-level interventions is also shown to correlate with the intensity of local drone adoption, even though the regulatory effect is slightly different among drone user groups (recreational vs. commercial). The data also paint a picture of the people living in neighborhoods with a high adoption rate of drones, who are on average younger, more affluent, and Whiter.

The paper proceeds as follows. Section 2 reviews the previous literature on the general scope of innovation diffusion, explains the dependence of drone technology and drone adoption on digital infrastructure, and articulates the complex relationship between regulation and innovation. Section 3 presents the data and methodologies applied in the study. Section 4 reviews the spatial-temporal patterns of drone diffusion and the regression results. Section 5 concludes and discusses the key implications of our results.

2.2 Literature Review

The birth and growth of cities are compounded by technological changes (Tarret et al., 1990). Technology can both strengthen the role of a city as an agent of domination and concentration and diminish the quality of life in the city with the introduction of certain side effects (Mumford, 1934). This perspective of technological determinism generates at least three concerns (Ellul, 1964): the adoption path of technology in society is predetermined, it is challenging to foresee all the consequences of technological advances, and technology demands that everything it produces be brought into a domain that affects the entire public. Emerging from the critique of technological determinism, the theory of the social construction of technology suggests that external social forces, especially social groups' attitudes and responses, affect the functionality and adoption of technology (Williams, 1996). Thus, the adoption of technology is not only associated with its characteristics but is also affected by a broad range of external factors. Given these general theoretical claims and accumulating empirical evidence, it is necessary to study both the technological and social constructs of drone proliferation as a way to understand the complex social-tech dynamics in the case of civil drone technology.

2.2.1 Determinants of innovation diffusion

Many theoretical frameworks have sought to describe the dynamic process of implementing innovations (Granovetter, 1973; Bandura, 1977; Rogers, 2003; Hassenzahl & Tractinsky, 2006). One of the most popular ideas has been Rogers's (2003) innovation diffusion theory, through which he introduced a four-element framework to investigate the diffusion process beyond geographical patterns. These four elements include innovation, communication channels, time span, and social system. Following Rogers's theory, a range of publications, mostly at the organizational level, have provided evidence on factors related to the decisions to adopt innovations and how the likelihood of adoption can be increased. Physical context is associated with adoption. For instance, it has been shown that urbanization and development may have a positive association with innovation adoption (Damanpour & Schneider, 2006; Meyer & Goes, 1988). The activeness and diversity of policies and regulations are also positively associated with adoption, including the specific enactment of policies, legislation, or regulations on innovation adoption (Aarons et al., 2011; Oldenburg & Glanz, 2008; Rogers, 2003). Similarly, during the mass adoption phase, legislation and accreditation standards have been associated with increased user adoption (Aarons et al., 2011; Berta et al., 2005; Feldstein & Glasgow, 2008). Finally, social networks and linkages with systems outside an organization have also been positively associated with adoption (Oldenburg & Glanz, 2008; Rogers, 2003; Valente, 1996). Innovations that are easy to use, better than current practice, observable, triable, cost-effective, compatible with users' norms and values, relevant, and low risk are more likely to be adopted (Rogers, 2003). Moreover, social climate and social influence, training readiness, cost-efficacy and feasibility, and other factors have been identified as having an impact on technology adoption (e.g., Meyers & Goes; Rogers, 2003).

The theory of innovation diffusion suggests that the diffusion of drone technology is a complex process involving numerous factors across different stages of adoption. Among the factors identified in previous studies, this study focuses on two major factors that have potentially affected drone adoption: digital infrastructure and regulatory interventions.

2.2.2 Digital infrastructure and the information divide

The availability and accessibility of digital infrastructure have multiple implications for innovation adoption in the digital age. While innovation diffusion theory emphasizes the important role of communication channels and information access in facilitating innovation adoption, digital divide research originated in the exploration of information inequality or the information gap (Rogers, 2003; Van Dijk, 2006). In the literature of communication science, the digital divide refers to a wide range of inequalities, including, for instance, life chances, resources, power, skills, and political participation (Sen, 1992). A popular aspect in this body o literature is technological opportunities, which has attracted numerous studies on physical access to computers and networks (e.g., Grubesic & Murray, 2005; Galperin & Greppi, 2018).

Even though the functions of traditional computers have been gradually replaced by smartphones and other mobile devices, access to the digital network still has a fundamental impact on our information access and (virtual) communication channels. According to Rogers's theory (2003), communication channels can be mass media or interpersonal networks, and "the internet has become more important for the diffusion of innovations in recent decades" (p. 18). Empirical studies have produced mixed results on the relationship between information capacity and innovation adoption. While some studies suggest that organizations with greater information capacities (e.g., channels and richness of information) tend to adopt innovations sooner (Wozniak, 1987; Fischer et al., 1996), other studies indicate that more comprehensive access to information may create stringent adoption criteria, which tends to increase the expected delay of adoption (Jenson, 1988).

Digital networks not only affect innovation adoption by creating communication channels and facilitating information sharing among individuals or organizations, but they have also become an integrated part of many internet-based innovations and activities. For instance, early adopters of the internet are more likely to become early owners of e-businesses (Zhu et al., 2006), and consumers with "higher amounts of internet use [for non-shopping activities] are associated with an increased amount of internet product purchases" (Varma Citrin et al., 2000, p. 294).

For drone technologies, digital networks facilitate the fast dissemination of the rich media products (e.g., aerial photos and videos) produced by drones. This virtual process of initial innovation adoption to media generation, information dissemination, and then further innovation adoption creates a self-reinforcing feedback loop toward the further adoption of drones. Moreover, drone technology is an integrated “system of systems.” Drones rely on the GNSS system to navigate and an onboard communication system to be remotely controlled. Moreover, the operation of drones relies on broadband networks, as drone operators have to frequently update firmware and edit their work with cloud-based software-as-a-service (SAAS) tools. Therefore, the present study recognizes the multifold roles of digital networks in innovation adoption and expects that the adoption of drones is also affected by the underlying digital infrastructure, such as broadband networks.

2.2.3 Regulation of innovations

Often, regulation is an instrument designed to channel behavior directly or indirectly and intentionally influence someone’s or something’s behavior (Butenko & Larouche, 2015). In the literature on regulation and technology, technology regulations are “based on the past and present technologic and economic reality, as well as social-cultural preferences” (Butenko & Larouche, 2015, p. 57), which creates an atmosphere that can both induce or impede innovation adoption (Ashford & Hall, 2011). The role of regulation in relation to innovation is to ensure the compliance of innovation with fundamental rights, maximize the positive effects, and minimize the negative effects (Brownsword & Somsen, 2009). For example, government regulations on energy consumption, emissions, and safety have spurred high rates of innovation in the automobile industry (Schulze et al., 2015).

Strict environmental regulations can induce efficiency and encourage innovations that improve the sustainability of development (Ashford & Hall, 2011).

Like many innovations, the proliferation of drones has also attracted growing regulatory attention at all levels of government in the United States. For safety and liability concerns, the FAA mandated drone registration in December 2015 and advised that state and local law enforcement agencies are often in the best position to manage drone activities (FAA, 2016). According to the National Conference of State Legislature (NCSL, 2020), at least 44 states have enacted laws addressing drones. While the federal laws provide a general framework with guidelines to regulate drones in the protected national airspace, state laws address more localized and law enforcement issues, including defining the scope of the regulation (e.g., what a drone or an unmanned aerial vehicle is), how they can be used by law enforcement or other state agencies, how they can be used by the general public, and regulations for their use in recreational or commercial activities (NCSL, 2020). While state governments have enacted various laws, their focal points are different. Some states have passed legislation that falls within the broad category of privacy, others have restricted drone access near critical facilities and infrastructure, and a handful of states have assembled special committees or advisory boards on drone regulation. However, less is known about how different types of state-level interventions affect different groups of drone users (e.g., recreational vs. commercial).

2.3. Data and Methodology

Since 2016, the FAA has released quarterly registration data for commercial drones and recreational drones, respectively. The data provide individual-level registration data by zip code, city, and state. Given that the data were individually collected and published without much cleaning, traditional string matching for a standardized dataset could only capture 81% of the total observations (approximately three million, four-year data in total). Therefore, this study treated this problem as a case of fuzzy string matching to increase the number of valid observations. The similarity score or Levenshtein distance between the "correct city-state" pair names and the error inputs was calculated using the "fuzzywuzzy" Python package (e.g., Los Angelos→Los Angeles, matching score 97). This study was able to capture 94% of observations when applying this fuzzy-matching technique. After this initial step of data cleaning, this study aggregated the data to the county level and combined the drone registration data with census variables and state-level interventions (binary variables). Specifically, the study included the following:

Dependent variables

Log of total registrations. Logged registrations for commercial drones, recreational drones, and total registrations.

Adoption rate (registrations/thousand population). To further investigate the pervasiveness of drone adoption, the study also considered the adoption rate for total drones and different types of drones.

Independent variables

Community characteristics are county-level census variables and represent the starting year (2016) of the study, as the best available data were included in the 2018 five-year estimate census data when the study was conducted. It is important to note that the quarterly-based drone registration data and the relatively short study period (2016–2019) generated some difficulties in creating a panel dataset. Neither collecting yearly-based census data for each county nor interpolating values for inter-census years was technically feasible.

Population density. The population density was calculated as thousand(s) per square mile.

Housing unit density. The number of housing units per square mile.

Median income. Logged form of median household income.

Percent non-White. Percentage of the non-White population.

Percent broadband. Percentage of households with broadband subscriptions.

State-level regulatory interventions. This study broke this variable down into three subcategories: privacy, infrastructure, and committee. Those falling into any of these categories were coded 1; those outside of these categories were coded 0.

Housing density categories. Housing density categories were defined as rural (< 16 units/sq. mi.), suburban (16–380.7 units/sq. mi.), and urban (> 380 units/sq. mi.), based on the categorization used by Allaire et al. (2018).

This study used spatial autocorrelation to identify spatial clusters of drone registrations across different periods of adoption. The optimized local Getis–Ord statistic was used to test the statistical significance of the clusters. The optimized distance was automatically detected using ArcGIS 10.3 software. To identify the changing patterns of hotspots over time, this study developed a matrix of hotspot changes. Further description and results are presented in Appendix A.

2.4. Results

2.4.1. Temporal and spatial trends

Although the majority of registrations are for recreational drones, the numbers of both recreational and commercial drones have grown geometrically in the past four years in the United States (Figure 2.1). The number of total registrations has seen a more than seven-fold increase from 210,000 to over 1.5 million. Registrations fluctuated over the study period, which could be attributed to a variety of factors, including regulatory changes, market changes, and data uncertainties. The study identified three major regulatory changes that might have affected the registration numbers. The first event was when the FAA mandated registration in December 2015 and officially launched the registration platform. The second regulatory event was the Taylor v. Huerta case, which challenged the FAA drone registration system and caused a temporary halt of the practice. However, a clear upward transition appeared in late 2018 when the National Defense Authorization Act (NDAA) reinstated the mandatory registration of drones.

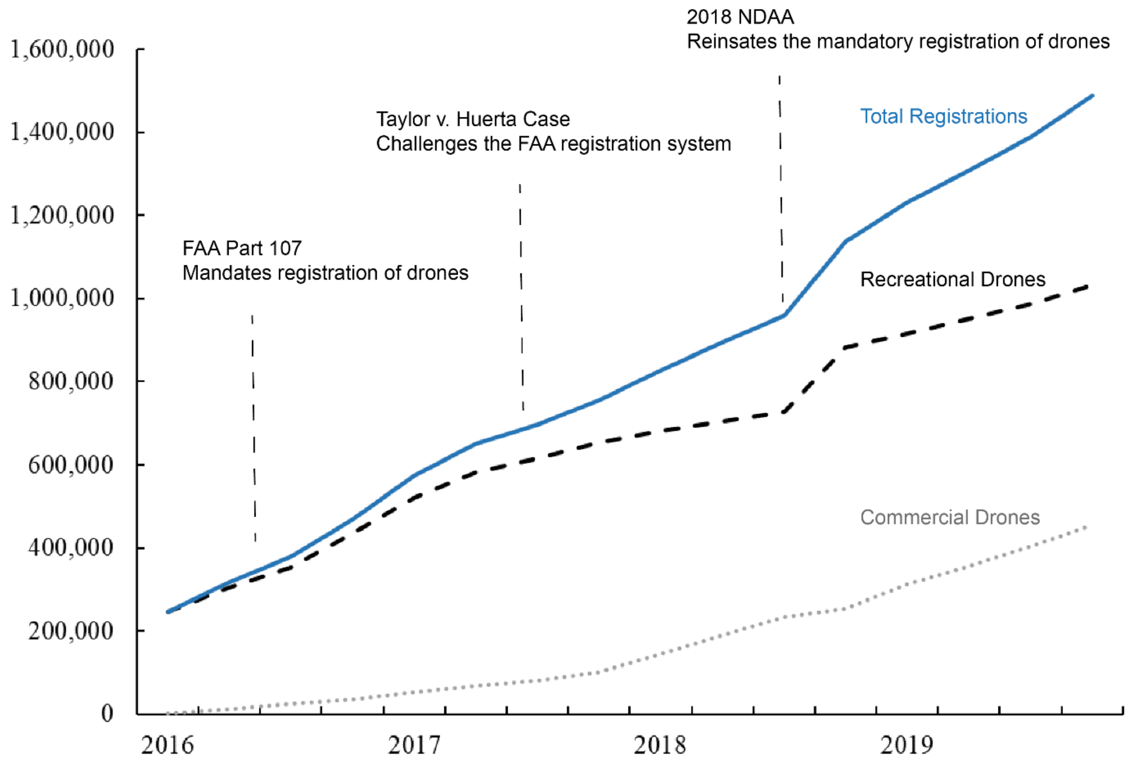

Figure 2.1. Key event and the quarterly change of drone registrations, 2016 - 2019

Registrations also varied across geographic locations. Figure 2.2 presents a map of the total registrations by drone usage at the county level. Some counties with the highest and earliest registrations are located in coastal areas, while inland counties trail behind. Southern California has witnessed a significant proliferation of both recreation and commercial drones, and this upward trend has intensified in the past few years. Recreational drone adoption expanded faster than that of commercial drones, reaching inland counties a few years earlier than the latter. However, this diffusion pattern is not a linear process, as the hotspot analysis (see Appendix A) indicates that the locations of statistically significant hotspots change periodically over time. More close-up investigations, such as time series analysis, are needed to untangle the periodic patterns of hotspots.

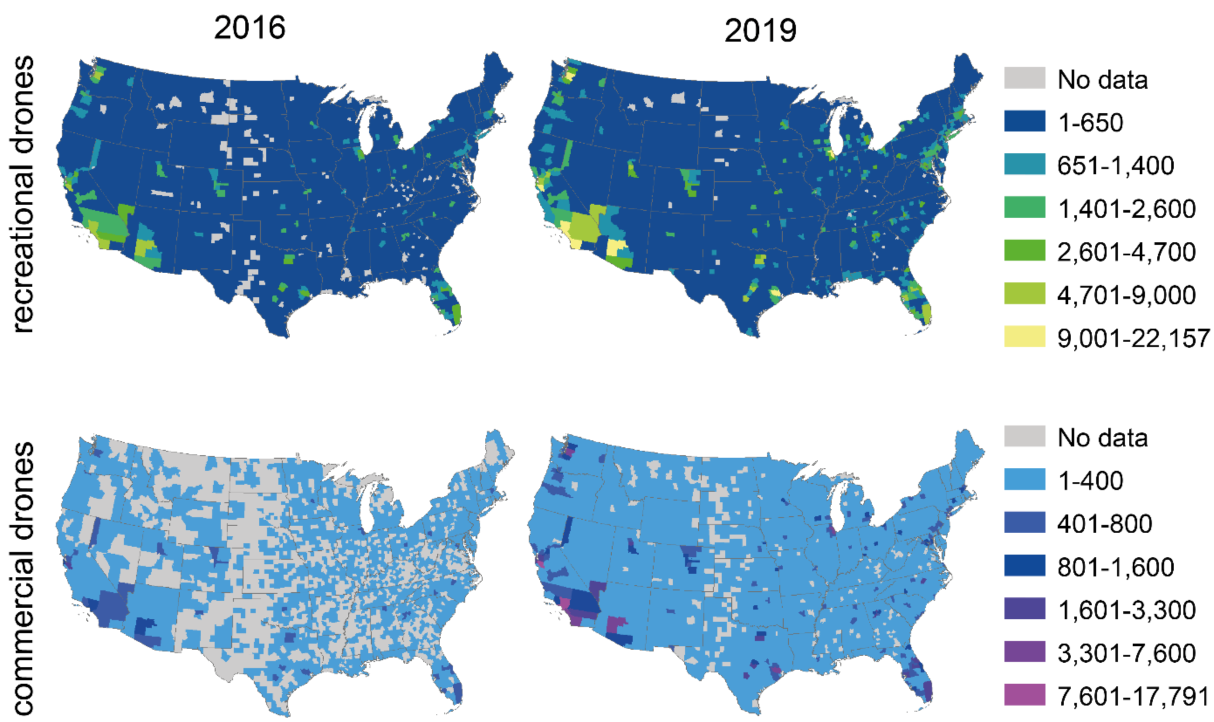

Figure 2.2 Recreational and commercial drone registrations, by county (2016 and 2019).

2.4.2. Regression results

The study presents two sets of OLS models for total registrations and adoption rate, respectively (see Table 2.1 and Table 2.2). The total registration explains the factors associated with the magnitude of innovation adoption, while the adoption rate models indicate factors associated with the pervasiveness of innovation adoption. Model 1 represents total drone registrations and the adoption rate, model 2 presents recreational drone registrations and adoption rate, and model 3 presents commercial drone registrations and adoption rate.

First, the availability of digital infrastructure and physical environment characteristics are associated with the adoption of drones. Regardless of the drone user group, the accessibility of broadband networks was positively correlated with drone adoption in all six models. The results might suggest that drone adoption is endogenously determined by digital infrastructure. Those with access to broadband networks not only have the necessary infrastructure to operate drones but also have a greater information capacity to become pioneers in innovation adoption. Also, built environment characteristics are associated with the likelihood of the adoption of recreational drones, as people living in lower density areas might be more likely to own this technology for recreational purposes. The built environment effect became insignificant in the commercial drone models but remained negative. As expected, the triability of innovation has been associated with the built environment (Rogers, 2003), as people living in low-density areas might be more likely to fly drones with fewer concerns to disrupt other people and less perceived operation risks (e.g., collisions or communication malfunctions due to physical obstacles or interruptions).

Second, regulatory interventions were significantly correlated with the adoption of drones. The availability of state-level committees and regulations on privacy and critical infrastructure was positively correlated with the adoption of recreational drones, indicating that higher adoption rate of drones might lead to the adoption of protective rules. Such effects on commercial drones remained largely consistent, but the availability of privacy regulation became an insignificant factor. In the adoption rate model, focusing on the pervasiveness of drone adoption, state-level regulations on critical infrastructure and the availability of special committees were insignificant factors but still had a positive direction.

Third, the results also paint a demographic picture of the people living in neighborhoods with a higher adoption rate of drones, who are on average younger, more affluent, and Whiter, although this does not necessarily mean that adopters of drones are consistent with the same demographic profiles.

Finally, the place type fixed-effect models suggested that the agglomeration of innovation adoption was still more likely to be in urban areas, where both the magnitude and pervasiveness of drone adoption are higher than in suburban and rural areas.

Table 2.1 Regression results with registration count (logged)

	Log Registrations					
	Model 1		Model 2		Model 3	
	No Fixed effect	Place type fixed effect	No Fixed Effect	Place type fixed effect	No Fixed Effect	Place type fixed effect
Pop.Density	0.493	0.355	0.492	0.339	0.474	0.268
	(0.324)	(0.330)	(0.322)	(0.328)	(0.433)	(0.438)
HousingUnit.Density	-1.775 *	-1.613 **	-1.754 *	-1.571 *	-1.537	-1.299
	(0.696)	(0.693)	(0.692)	(0.689)	(0.932)	(0.921)
Age	-0.118 ***	-0.109 ***	-0.117 ***	-0.108 ***	-0.153 ***	-0.138 ***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.012)	(0.012)
Log.Income	3.645 ***	4.012 ***	3.679 ***	4.053 ***	2.554 ***	3.116 ***
	(0.247)	(0.243)	(0.245)	(0.241)	(0.330)	(0.323)
Percent.NonWhite	-2.641 ***	-3.051 ***	-2.573 ***	-2.995 ***	-2.229 ***	-2.854 ***
	(0.241)	(0.243)	(0.240)	(0.242)	(0.323)	(0.323)
Percent.Broadband	4.841 ***	1.999 **	4.526 ***	1.634 *	10.734 ***	6.381***
	(0.740)	(0.761)	(0.736)	(0.757)	(0.991)	(1.011)
State.Privacy	0.196 *	0.248 **	0.181 *	0.233 **	0.135	0.214
	(0.089)	(0.087)	(0.089)	(0.087)	(0.120)	(0.116)
State.Infrastructure	0.955 ***	0.982 ***	0.954 ***	0.983 ***	0.949 ***	0.990 ***
	(0.111)	(0.108)	(0.110)	(0.108)	(0.148)	(0.144)
State.Committee	0.378 ***	0.316 **	0.388 ***	0.326 ***	0.618 ***	0.523 ***
	(0.093)	(0.091)	(0.092)	(0.090)	(0.124)	(0.121)
(Urban)						
Suburban		0.162		0.126		0.268
		(0.279)		(0.277)		(0.371)

Rural		-1.025 ***		-1.076 ***		-1.553 ***
		(0.289)		(0.287)		(0.383)
Constant	-33.626 ***	-35.325 ***	-34.143 ***	-35.838 ***	-26.628 ***	-29.248 ***
	(2.385)	(2.339)	(2.373)	(2.325)	(3.193)	(3.107)
R-squared	0.397	0.426	0.393	0.424	0.317	0.358
Prob > X^2	0.000	0.000	0.000	0.000	0.000	0.000
Observations	3219	3219	3219	3219	3219	3219

Notes: Standard errors are in parentheses.

* Significance level of 0.05, ** Significance level of 0.01, *** Significance level of 0.001.

Table 2.2 Regression results with adoption rate (registrations per thousand population)

	Adoption Rate (Registrations/thousand population)					
	Model 1		Model 2		Model 3	
	No Fixed effect	Place type Fixed effect	No Fixed effect	Place type Fixed effect	No Fixed effect	Place type Fixed effect
Pop.Density	0.470	0.118	0.304	0.074	0.165	0.044
	(0.314)	(0.327)	(0.219)	(0.228)	(0.121)	(0.126)
HousingUnit.Density	-1.118	-0.596	-0.745	-0.404	-0.374	-0.192
	(0.675)	(0.688)	(0.470)	(0.479)	(0.260)	(0.266)
Age	-0.014	-0.016	-0.003	-0.004	-0.011 **	-0.012 **
	(0.009)	(0.009)	(0.006)	(0.006)	(0.003)	(0.003)
Log.Income	1.976 ***	2.028 ***	1.528 ***	1.563 ***	0.448 ***	0.464 ***
	(0.239)	(0.241)	(0.167)	(0.168)	(0.092)	(0.093)
Percent.NonWhite	0.037	-0.154	-0.136	-0.262	0.172	0.108
	(0.234)	(0.241)	(0.163)	(0.168)	(0.090)	(0.093)
Percent.Broadband	8.469 ***	8.199 ***	5.199 ***	5.010 ***	3.270 ***	3.188 ***
	(0.718)	(0.755)	(0.500)	(0.526)	(0.277)	(0.292)
State.Privacy	0.413 ***	0.408 ***	0.268 ***	0.265 ***	0.145 ***	0.143 ***
	(0.413)	(0.087)	(0.060)	(0.060)	(0.033)	(0.033)
State.Infrastructure	0.125	0.155	0.118	0.138	0.006	0.017
	(0.107)	(0.107)	(0.075)	(0.075)	(0.041)	(0.041)
State.Committee	0.098	0.110	0.043	0.051	0.055	0.060
	(0.090)	(0.090)	(0.063)	(0.063)	(0.035)	(0.035)
(Urban)						
Suburban		-1.058 ***		-0.689 ***		-0.369 **
		(0.277)		(0.193)		(0.107)
Rural		-1.018 ***		-0.668 **		-0.350 **
		(0.286)		(0.199)		(0.111)
Constant	-23.383 ***	-22.610 ***	-17.554 ***	-17.057	-5.829 ***	-5.553 ***
	(2.314)	(2.321)	(1.611)	(1.616)	(0.893)	(0.896)
R-squared	0.261	0.265	0.254	0.257	0.200	0.203
Prob > X^2	0.000	0.000	0.000	0.000	0.000	0.000
Observations	3219	3219	3219	3219	3219	3219

Notes: Standard errors are in parentheses.
* Significance level of 0.05, ** Significance level of 0.01, *** Significance level of 0.001.

2.5 Conclusion and discussion

Innovation diffusion is a complex and dynamic process in which numerous factors may affect the adoption status at different stages of the process. The arrival of the digital age has transformed the ways through which people communicate and disseminate information. Therefore, digital infrastructure has become increasingly dominant in facilitating innovation diffusion and has occupied an integrated part of many emerging technologies. Additionally, the relationship between technology and regulation has for decades been investigated by academic and professional researchers. However, the arrival of each new yet disruptive form of technology has brought new regulatory challenges for its effective management while also nurturing an environment that encourages further innovation.

Drone technology, taking the form of a digitally connected and remotely controlled unmanned system, has attracted growing attention from the public and private sectors given its advantages in many professional applications and disruptions in the urban environment. The proliferation of drones has rapidly expanded from coastal regions to most areas in the United States. Notably, Southern California is a pioneer and the most intensified hotspot of drone adoption by different means of measurement. Moreover, in the present study, the availability of digital infrastructure is positively associated with the magnitude and pervasiveness of drone adoption. This finding might suggest that the innovation divide can be further exacerbated with the arrival of emerging technologies, as digital networks function as information access and an integrated part of many disruptive technologies. The density of the built environment has also been found to be associated with drone adoption. This finding is consistent with the innovation diffusion theory, as perceived triability and operation risks affect user choices (Rogers, 2003).

Beyond the close relationship between the digital/built environment and drone adoption, the study also found that some regulatory interventions were correlated with the likelihood of drone adoption, even though the effects varied across different user groups. Nevertheless, the study needs to be cautious in interpreting this relationship, as we still need more close-up investigations to make causal inferences. Besides, the study still does not know the effectiveness of these state-level regulations (e.g., does the critical infrastructure protection law reduce drone intrusions?). Moreover, urban areas remain the center of innovation agglomeration in the case of drones, with all other factors held constant.

Several policy implications emerge from our findings. First, closing the gap in the digital divide could benefit communities lagging in the digital age and promote the adoption of emerging technologies. The provision of digital infrastructure not only empowers communities with greater information capacity but also lays a foundation for the arrival of digitally connected technologies. Second, coordination between state agencies and learning from the best regulatory practices could provide a more consistent and effective response to emerging challenges related to drone proliferation. Third, more research and regulatory attention should be paid to the local-level management of drones, given the decentralized and mobilized features of drones.

Chapter 3. Spatial patterns of drone adoption: Insights from communities in Southern California

3.1 Introduction

Cities utilize technological innovations to address major societal challenges and improve efficiencies in urban environmental management. In the past decade, cities have seen an increase in autonomous technology from the surface to the air, which can be viewed as a disruptive technology, defined by its novelty, rapid growth, prominent impact, and future uncertainty (Rotolo et al., 2015). Drone technology is one such example that is being increasingly integrated into the urban environment for various purposes. From 2016 to 2020, the total number of drone registrations increased from 300,000 to over 1.5 million in the United States (US) (Federal Aviation Administration [FAA], 2020). Although recreational drones account for most of the total registrations, commercial drones are also on the rise. Drone technology has great promise in urban planning, in addition to industrial applications in surveillance, film-making, and agriculture. It is becoming an increasingly vital tool to collect high-quality, accurate, and timely data to analyze sites and make data-driven decisions (Stephens et al., 2020). Drone data have been used for mapping, 3D modeling, and design to support a variety of planning activities, including transportation as well as environmental and disaster planning. Despite the increasing interest in the potential applications of drones, there is a lack of research on how widely drone technology has been adopted, and how various socioeconomic and spatial factors affect drone adoption.

In the context of innovation diffusion, individual behaviors are affected by various aspects such as innovation characteristics (observed and perceived), communication channels, time span, and social systems (Rogers, 2003). While innovation diffusion theory emphasizes the essential role of communication channels and access to information to prompt innovation adoption, the research on the digital divide originated from the exploration of information inequality or information gaps (Rogers, 2003; Van Dijk, 2006). Many studies have explored how various factors affect innovation adoption and how the accessibility of information and communication technology (ICT) infrastructure varies across space and between racial and ethnic groups (see Fairlie, 2004; Grubesic, 2003). However, questions about how the digital divide affects innovation adoption remain unexplored. The adoption of drone technology presents a unique opportunity to examine these questions, as ICT infrastructure serves as both a channel for users to access innovation information and as an essential infrastructure for the operation of drones.

This study contributes to the literature by applying spatial regression models to explore the distribution of drone adoption across communities (zipcodes) in Southern California. The study focuses on individually owned non-professional drones (i.e., hobby drones), which account for 78% of the total drone registration in the study area (FAA, 2020); the study does not explore the adoption of commercial and public-use drones related to organizational behaviors. Moreover, the study investigates the association between drone adoption and the factors covering socioeconomic, ICT infrastructure, occupational, and land use characteristics in the communities. The next section reviews the connections between innovation diffusion theory and the digital divide literature to assess previous studies of potential factors associated with drone adoption. The third section describes the study data and methodology; it then presents several spatial regression models that estimate the effects of various factors on drone adoption while considering the spatial heterogeneity of drone users. The final section presents the conclusion and policy implications of the findings.

3.2 Literature review

3.2.1 The determinants of civilian drone adoption

Scholars have paid increased attention to the proliferation and management of civilian drones in recent years, and have systematically examined how public-use drone users perceive the use of drones as well as the associated risks or benefits (Nelson et al., 2019; Reddy and DeLaurentis, 2016). Recent studies have consistently indicated that the public is concerned about their safety and privacy when it comes to the use and regulation of drones globally (Anania et al., 2019; Nelson et al., 2019; Rice et al., 2018; Wang et al., 2016). While civilian drones have been used for commercial, recreational, and law enforcement purposes, the public believes that recreational and law enforcement drones need more monitoring and regulation (Boucher, 2015). Public perceptions can vary depending on drone user groups, applications, and associated risks (Aydin, 2019). Clothier et al. (2015) found that an Australian focus group viewed drones to be as risky as existing manned aviation. However, although law enforcement drones have been a prior public concern, operating a law enforcement drone over a black community is perceived as being more acceptable by a convenience sample of participants from the United States than over a primarily white community (Anania et al., 2019).

While these perceptual factors have emerged in survey-based studies and reflect an emerging social construct around drone adoption, certain sociodemographic characteristics have also been associated with early drone adoption. For example, Reddy and DeLaurentis's (2016) drone stakeholder sample (comprised of drone researchers, professionals, and hobbyists) was made up of young adults who were better educated and more informed about unmanned aircraft than the public sample (i.e., non-users). However, there was no significant difference between the views of the public with an educational background in science, technology, engineering, or mathematics (STEM) and non-STEM participants' views toward drones (Aydin, 2019). Meanwhile, in a nationwide survey on unmanned aircraft vehicles (UAV) in the US (Nelson et al., 2019), Asian respondents were over-represented and both Black and Hispanic populations were under-represented among drone adopters when compared with the national average. Since Nelson et al.'s (2019) sample was too small to make confident inferences about the racial and ethnic characteristics of the drone users, it is worth exploring the potential racial and ethnic disparities in drone adoption. Further, perceptions about drone usage have been associated with land use and spatial contexts. Lin Tan et al. (2021) found that the acceptance of drone usage among 1050 Singaporean residents was lowest in residential areas and highest in industrial areas. The perceived level of operational risk in disparate land use contexts could be attributed to the association between drone acceptance levels and land use contexts.

Although the early empirical studies have shed light on multiple categories of factors (e.g., socioeconomic, racial and ethnic, land use, and locational characteristics) that are potentially related to drone adoption, the study considers the adoption of civilian drones in the context of digital-age innovation adoption to contribute more theoretical insight to the literature. The study pays special attention to continued zipcode level racial and ethnic disparities in drone innovation adoption and the connection between the digital divide and technological opportunities.

3.2.2 Racial and ethnic disparities in innovation adoption

The racial and ethnic disparity in innovation adoption is a lasting phenomenon. In the context of urban studies, racial segregation refers to the concentrated poverty and intergenerational socioeconomic disadvantages of minority groups (Quillian, 2012). Historically, racial segregation in the postwar housing market trapped many African Americans within inner-city communities in a vicious cycle which included underinvestment in infrastructure, limited access to public goods, and fewer life opportunities (Massey, 1990). The systematic disadvantages of minority groups have also been identified in many studies on the adoption of ICT. Even when controlling for socioeconomic factors, African Americans and Latinos have a lower rate of access to and skills in ICT in the US (Mossberger et al., 2006). Although some scholars have argued that this gap in access to ICT will narrow as adoption becomes more saturated (see Van Dijk, 2003), more recent studies have shown that unequal access to and usage gaps in broadband infrastructure persist in many low-income and minority neighborhoods (Galperin et al., 2021; Van Dijk, 2006). These findings have prompted the current study to investigate whether and how the adoption of civilian drones varies across historically marginalized communities, defined based on zipcode areas of aggregation. The study focuses on Southern California for two reasons. First, historical racial segregation policies, such as redlining, have been identified as a persistent factor that affects many life opportunities of the Black and Latino populations in the region (Galperin et al., 2021; Lewis et al., 2005). Second, the region has the highest number of registered civilian drones per capita among the metropolitan areas in the US (FAA, 2020). Therefore, the study investigates whether community-level racial and ethnic disparities exist in the adoption of drones in a region that has an overall relatively high rate of adoption.

3.2.3 Connecting the digital divide to innovation adoption

While the digital divide literature has extensively explored the factors related to the digital divide, Van Dijk (2006) suggests that it has paid insufficient attention to the consequences of the observed digital divide, and questions on whether the digital divide has resulted in the lower utilization of new technological opportunities (Van Dijk, 2003). An early study on the digital divide found that "as the diffusion of mass media information into a social system increases, segments of the population with a higher socioeconomic status tend to acquire this information at a faster rate than the lower status segments" (Tichenor et al., 1970: 159). More recent studies have found the persistent digital divide has a significant impact on people's access to knowledge, education opportunities, and social and political participation opportunities (see Shelley et al., 2004; Sylvester and McGlynn, 2009). Based on these findings and theoretical implications, the study argues that the persistent digital divide combined with the lasting effects of urban segregation may have magnified the gap in knowledge of emerging drone technology between the information-rich and information-poor. Broadband infrastructure serves as a channel through which to disseminate information generated by drone users (e.g., images and videos captured by users) and is an essential infrastructure for drone operations (e.g., data links and navigation maps). Therefore, this study investigates whether there are significant associations between the provision of broadband infrastructure and the adoption of drones.

3.3 Data and Methodology

Taking the case of drone technology, this study explored how ICT infrastructure, socioeconomic, occupational, and land use characteristics affect the adoption of an emerging disruptive technology. Accordingly, this study constructed a zip code-level database for communities in Southern California to capture our variables of interest. To control for the spatial dependence effect, the study estimated spatial regression models and compared the results with those from the ordinary least squares (OLS) models.

3.3.1 Study area

This study analyzed the zipcode level drone adoption rate from 2015 to 2019 in Southern California (Los Angeles County, Orange County, Ventura County, San Bernardino County, and Riverside County). This region is a significant and constant hotspot for drone adoption in the US. Figure 3.1 presents the spatial distribution of the drone adoption rate across the Southern Californian communities. Within the study period, both the US and the study area saw a significant proliferation in civilian drones, thus the FAA began to publish quarterly drone registration data.

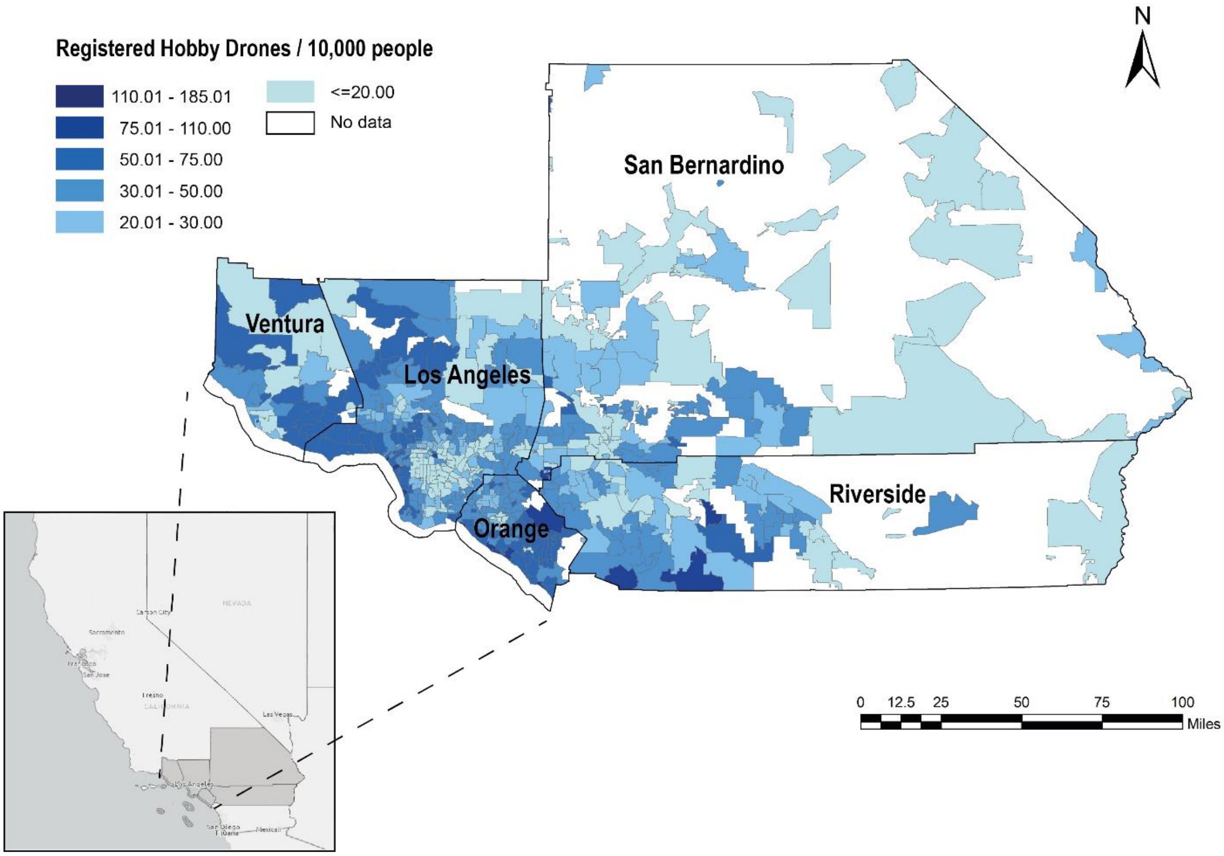

Figure 3.1 Number of registered hobby drones per 10,000 people, 2015-2019
Source: The FAA sUAS registration database.

3.3.2 Data

This study used the drone registration data from the FAA Small Unmanned Aircraft System (sUAS) registration database to create the dependent variable. The data were downloaded from the FAA in February 2020, and the study used the total registrations from 2015 to 2019.

The explanatory variables included socioeconomic, ICT infrastructure, occupational, and land use characteristics. Zipcode level data on the neighborhood socioeconomic characteristics, such as the median age, household income, and people of color, were collected from the American Community Survey (2014–2018: five-year estimates). The study chose household coverage of high-speed broadband (minimum of 25 Mbps download and 3 Mbps upload speeds) as an essential metric to measure both technological infrastructure and people's access to information related to innovation. We collected the zipcode level neighborhood availability of high-speed broadband data from the California Public Utility Commission (CPUC), which provides annual datasets on the availability of local digital infrastructure. Based on the 2016 parcel-level land use data from the Southern California Association of Governments (SCAG), the study aggregated land use categories at the Zip Code Tabulation Area (ZCTA) level to support the inferences made at the community level. As early studies indicated that the acceptance levels of drone usage varied by land uses (e.g., Lin Tan, 2021), this study incorporated the percentage of residential land use (*Pct.Residential*), percentage of open space and recreation land use (*Pct.Openspace&Recreation*), and percentage of office and commercial land use (*Pct.Office&Commercial*) to reflect on the distribution of drones across major types of land uses in the study area.

Table 3.1 Data and variables

Category	Variable	Description	Data source	Geographical unit
Dependent variable	Hobby drone adoption rate (DV)	Number of registered hobby drones/10k population	FAA	ZCTA
Socioeconomic characteristics	Age	Median age	Census	ZCTA
	Age.Sq	Median age (squared)	Census	ZCTA
	Log.Income	Median income (logged)	Census	ZCTA
	Pct.NonWhite	Percentage of not	Census	ZCTA
		non-Hispanic	Census	ZCTA
	Pct.Hispanic	White	Census	ZCTA
		Percentage of non-White Hispanic population	Census	ZCTA

	Pct.Black	Percentage of Black population		
	Pct.Asian/PI	Percentage of Asian and Pacific Islander population		
Tech infrastructure	Pct.HighSpeedBroadband	Percentage of census block groups with access to high-speed broadband (minimum 25 Mbps download and 3 Mbps upload speeds)[1]	California Public Utilities Commission	Census block group
Occupation	Pct.TechWorkers	Percentage of employed population working in computer, engineering, and science occupations	Census	ZCTA
	Pct.ArtsWorkers	Percentage of employed population working in arts, design, entertainment, sports, and media occupations	Census	ZCTA
Land use	HousingUnit.Density	Housing unit density in thousands/sq mi	Census	ZCTA
	Pct.Residential	Percentage of residential land parcels	SCAG	Land parcel
	Pct.Openspace&Recreation	Percentage of open space and recreational land parcels	SCAG	Land parcel
	Pct.Office&Commercial	Percentage of office and commercial land parcels	SCAG	Land parcel
	Coast	1: Coastal community; 0: non-coastal community	Census TIGER	ZCTA

[1] According to the Federal Communications Commission (FCC), the benchmark speed of high-quality broadband is 25 Mbps download/3 Mbps upload (25 Mbps/3 Mbps) for fixed services (https://www.fcc.gov/reports-research/reports/broadband-progress-reports/2018-broadband-deployment-report).

Table 3.2 Descriptive statistics of the variables (*n=572*)

Variable	Mean	S.D.	Min	Max
Hobby drone registration/10k pop.	35.04	21.82	0	186.92
Age	37.67	7.80	0	68.04
Log.Income	11.13	0.39	9.63	12.26
Pct.NonWhite	0.59	0.26	0	1.00
Pct.Hispanic	0.38	0.01	0	1.00
Pct.Black	0.06	0.00	0	1.00
Pct.Asian/PI	0.12	0.01	0	0.72
Pct.HighSpeedBroadband	0.58	0.16	0	0.99
Pct.TechWorkers	0.05	0.03	0	0.21
Pct.ArtsWorkers	0.04	0.04	0	0.25
Housing.Density (thousands/sq mi)	2.15	2.61	0	21.60
Pct.Residential	0.76	0.25	0	1.00
Pct.Openspace&Recreation	0.02	0.07	0	0.88
Pct.Office&Commercial	0.05	0.09	0	0.96
Coast (0/1)	0.07	0.25	0	1

3.3.3 Analytical frameworks and models

This study employed spatial regression models to identify how the various factors influenced the zipcode level adoption of drones while controlling for the spatial dependence effects. Innovation adoption was determined by a range of factors. This study explicitly tested the contribution of zipcode level ICT infrastructure, occupational, socioeconomic, and land use characteristics on the adoption of drones in Southern California communities. The conceptual model of our analysis is as follows:

$$A = f(T, O, S, L, e) \quad \text{..} (1)$$

where A (the drone adoption rate) is a function of T (technological infrastructure), O (occupation), S (socioeconomic characteristics), L (land use characteristics), and e (error term).

The innovation adoption literature has suggested that innovation adoption is spatially dependent. For example, the spillover effect of knowledge and spatially bound social networks can both increase the possibility of local innovation adoption. Additionally, adoption may be spatially dependent if factors unobserved in the available data affect the adoption of innovation in adjacent zipcodes. The study confirmed the existence of such effects in our model by using Moran's I and the Lagrange multiplier (LM) tests and employed spatial regression models to account for spatial dependence. This study compared the results of these spatial regression models with the OLS regression models. The spatial lag model (SLM) helped us explore the spatial dependence effect in the dependent variable, while the spatial error model (SEM) helped us to understand the spatial dependence effects from the unobserved variables. The geographically weighted regression (GWR) further enabled us to check the spatial non-stationarity of the independent variables by incorporating local spatial relationships. The goodness-of-fit of the models was evaluated using various statistical tests (Anselin, 1988), such as the LM test and the Akaike information criterion (AIC).

Spatial Lag Model (SLM)

Compared with the global linear regression model (or OLS model), the SLM assumes that spatial dependence exists in the dependent variable (Anselin, 1988). The SLM controls for the influence of the values of the dependent variables in nearby observations through a predefined spatial weights matrix. The model is expressed as follows:

$$y = \rho W y + X\beta + \varepsilon \qquad (2)$$

where y is a vector of observations on the dependent variable, X is a matrix of observations on the independent variable, β is a vector of coefficients, W is a standardized spatial weights matrix that defines the spatial interactions among communities, ρ represents the coefficients of the spatially lagged dependent variables, and ε is a vector of error terms. The weights matrix and the spatially lagged dependent variable (ρW) capture the potential spillover effects from nearby communities.

Spatial Error Model (SEM)

Conversely, the SEM is particularly suitable for testing the spatial dependence effect in the error terms (Anselin, 1988). The model is expressed as follows:

$$y = X\beta + \varepsilon \qquad (3)$$

$$\varepsilon = \lambda W \varepsilon + u \qquad (4)$$

where ε is a vector of spatially autocorrelated error terms. In contrast to the SLM, the SEM recognizes the spatial dependence of the error term of an observation and its corresponding neighbors, as some of the variables that spatially influence the dependent variable might not be included in the model.

Geographically Weighted Regression (GWR) Model

The study also employed a GWR model to address the complex spatial variation of parameters. The GWR is formulated like the OLS, but its coefficients are location specific. The equation for the GWR is expressed as follows:

$$D = \beta_i Z + \varepsilon_i \quad \text{..} \quad (5)$$

where β_i represents a vector of locally estimated coefficients for the local observation i, ε_i is the corresponding error term, and Z is the weighting matrix for each observation i and greater weights are placed on closer observations. Because the GWR assumes that the relationship between the dependent and independent variables differs across locations, its estimation is sensitive to the bandwidth of the spatial kernel (Fotheringham et al., 2002). This study calculated the optimal bandwidth by minimizing the AIC using Stata 14.

3.4 Results

3.4.1 Spatial patterns of drone adoption

Figure 3.1 shows that the drone adoption rate in coastal areas, Orange County, and the western part of Los Angeles County is higher than the region's average adoption rate. Further, this spatial distribution map suggests that clustering patterns of the drone adoption rate might exist in the region. To explore the spatial autocorrelation of the adoption rate of hobby drones, the study built a spatial weights matrix using inverse distance weighting (greater weights for observations closer to the targeted location). Then, this study used this matrix to calculate the global and local Moran's I. The results show that the global spatial autocorrelation effect is positively significant (global Moral's I=0.074, Z-score=20.283, *p*=0.000). The local Moran's I result indicates that the drone adoption hot spots are clustered in coastal areas, especially in Orange County and Ventura County (see

Figure 3.2), while cold spots are more likely to be found in inland communities. More importantly, the Moran's I analysis reflects significant spatial non-stationarity in the dependent variable. Using local spatial autocorrelation analysis, four distinct cluster types are generated to reflect the clustering patterns of drones: high-high, low-low, low-high and high-low. High-high clusters include zipcodes with higher than average rates surrounded by other zipcodes with higher than average rates. Similarly, low-low clusters include zipcodes with lower than average rates surrounded by other zipcodes with lower than average rates. Low-high and high-low clusters are developed in a similar fashion.

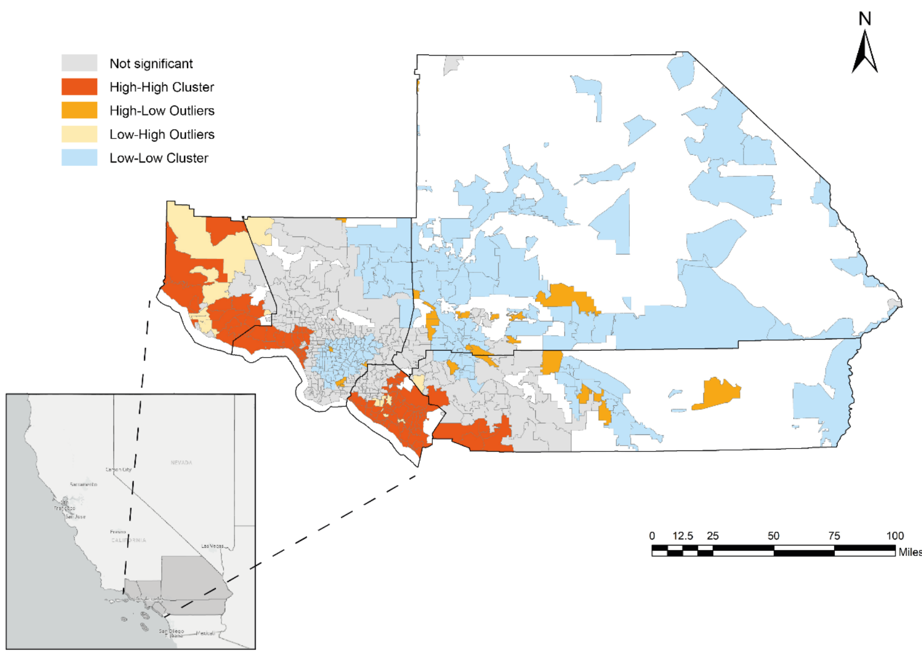

Figure 3.2 Local spatial autocorrelation analysis of clusters and outliers of hobby drone adoption in Southern Californian communities

3.4.2 Model comparisons

To explore how the various factors influenced the adoption of drones while considering the spatial dependence effects, the study employed three spatial regression models (SLM, SEM, and GWR) and compared the results with an OLS model (see Tables

3.3a and Tables 3.3b). The OLS estimation provides 12 global parameters (plus one intercept) that reflect the effect of each explanatory variable on the drone adoption rate. The SLM and SEM estimations provide additional parameters that reflect the effect of spatial dependency on the dependent variable and error term, respectively. Both LM tests, derived from the SLM and SEM, show the applicability of the models. The goodness-of-fit tests (R-squared and AIC) suggest that compared with the OLS model, the SLM and SEM are more appropriate for modeling the dynamics of drone adoption by controlling the spatial dependence effect. Moreover, the GWR shows several local patterns in the distribution of the parameters which are not seen in the global models.

According to our results from the OLS, SLM, and SEM, multiple variables have a consistent significant impact on the adoption of hobby drones across the different models. For example, *Age* and *Log.Income* are positively associated with a higher adoption rate, while *Age.Sq* has a negative effect on drone adoption. These results indicate that areas that have are economically well-off and have more young adults are associated with higher drone adoption rates. Moreover, the percentage of populations of color (*Pct.NonWhite*) was significantly associated with lower adoption rates of drone technology when other factors are held constant. Further, the supplementary analysis (see Appendix A) shows that among the populations of color both *Pct.Black* and *Pct.Hispanic* have a significant negative association with the drone adoption rate, while *Pct.Asian.PI* has a negative association but is insignificant at the 5% level. Another notable consistent pattern is that high-speed broadband coverage (*Pct.HighSpeedBroadband*) is positively associated with the adoption of drone technology. The magnitude of the broadband impact slightly decreases (but is still significant) when the study controls for the spatial heterogeneity effects of drone adoption.

Further, areas with more workers in the technology and arts sectors (*Pct.TechWorkers* and *Pct.ArtsWorkers*) are associated with higher adoption rates. Among the land use factors, *Pct.Residential* is negatively associated with drone adoption, while other land use factors appear to have no substantial effect. Moreover, the spatial dependence effects in the SLM are explicit and statistically significant. By holding all other factors constant, the study expects an increase of 0.68% in the adoption rate in a zip code area if the weighted average of the drone adoption rate for the neighboring zip codes increases by 1%.

The regression coefficients summarized in Table 3.3b and Figure 3.3 exhibit the significant variations across the study area. Moreover, the directions of the coefficients change for some of the independent variables in some areas. For example, although *Pct.Residential* is consistently and negatively associated with drone adoption in the global regression models, the GWR results suggest that this effect has a significant spatial variation. Figure 3.3 indicates that the negative association between *Pct. Residential* and adoption rate diminishes and switches to positive in communities away from the coastal regions. Similar spatial non-stationarity for other parameter estimates such as *Age* and *Pct.NonWhite* has been identified in the Figure 3.3 where dark colors indicate a positive association.

Table 3.3a Comparison of OLS, SLM, and SEM results

Variable (N=572)	OLS		SLM		SEM	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Hobby drone adoption rate (DV)						
Age	2.634 ***	0.290	2.597 ***	0.281	2.578 ***	0.287
Age.Sq	-0.031 ***	0.004	-0.030 ***	0.004	-0.031 ***	0.004
Log.Income	18.353 ***	2.098	15.577 ***	2.110	17.502 ***	2.194
Pct.NonWhite	-22.115 ***	3.640	-20.579 ***	3.540	-21.965 ***	3.795
Pct.HighSpeedBroadband	10.713 *	4.541	8.548 *	4.293	10.433 *	4.425
Pct.TechWorkers	95.351 ***	22.471	86.652 ***	21.843	92.573 ***	22.866
Pct.ArtsWorkers	68.779 **	21.889	67.041 **	21.211	88.124 ***	23.758
Housing.Density	0.317	0.330	0.110	0.322	0.277	0.342
Pct.Residential	-12.976 ***	3.301	-12.903 ***	3.199	-12.822 ***	3.339
Pct.Openspace&Recreation	-20.355 *	10.066	-6.307	10.161	-15.260	11.809
Pct.Office&Commercial	0.773	8.335	3.976	8.102	0.810	8.178
Coast	13.594 ***	2.628	11.830 ***	2.571	10.310 ***	2.801
Intercept	-209.077 ***	23.105	-200.663 ***	22.452	-195.198 ***	24.401
Rho/lambda			0.683 ***	0.139	0.768 ***	0.166
R-squared	0.559		0.586		0.554	
LM			24.754 ***		7.936 **	
AIC	4707.057		4681.332		4701.419	

Note: * significance level of 0.05, ** significance level of 0.01, *** significance level of 0.001

Table 3.3b Distribution of GWR coefficients

	GWR coefficients				
	Mean	**Std. Dev.**	**Min**	**Max**	**Non-stationarity**
Hobby drone adoption rate (DV)					
Age	2.883	1.086	-5.659	6.417	1.086 *
Age.Sq	-0.031	0.017	-0.097	0.112	0.017
Log.Income	12.914	7.791	-66.292	69.170	7.791
Pct.NonWhite	-32.053	9.290	-51.801	62.281	9.29 *
Pct.HighSpeedBroadband	15.958	14.181	-59.801	124.369	14.181
Pct.TechWorkers	83.677	45.375	-102.405	404.497	45.375
Pct.ArtsWorkers	63.823	55.318	-170.617	736.617	55.318
Housing.Density	0.111	1.723	-19.421	14.055	1.723
Pct.Residential	-8.810	6.700	-95.852	30.628	6.689 **
Pct.Openspace&Recreation	15.012	26.505	-77.031	100.242	26.505
Pct.Office&Commercial	17.909	23.460	-69.723	327.254	23.460
Intercept	-162.600	86.128	-768.213	673.408	86.128 *

Note: The dummy variable *Coast* was not included in the GWR model because the GWR allows for the explanatory variable coefficients to vary spatially, so the spatial regime explanatory variables are unnecessary and, if included, create problems with local multicollinearity. Significance tests for non-stationarity compare the standard deviations of the observed parameter estimates with those from the Monte Carlo simulation.
* Indicates the significance levels of spatial non-stationarity; * significance level of 0.05, **

significance level of 0.01, *** significance level of 0.001

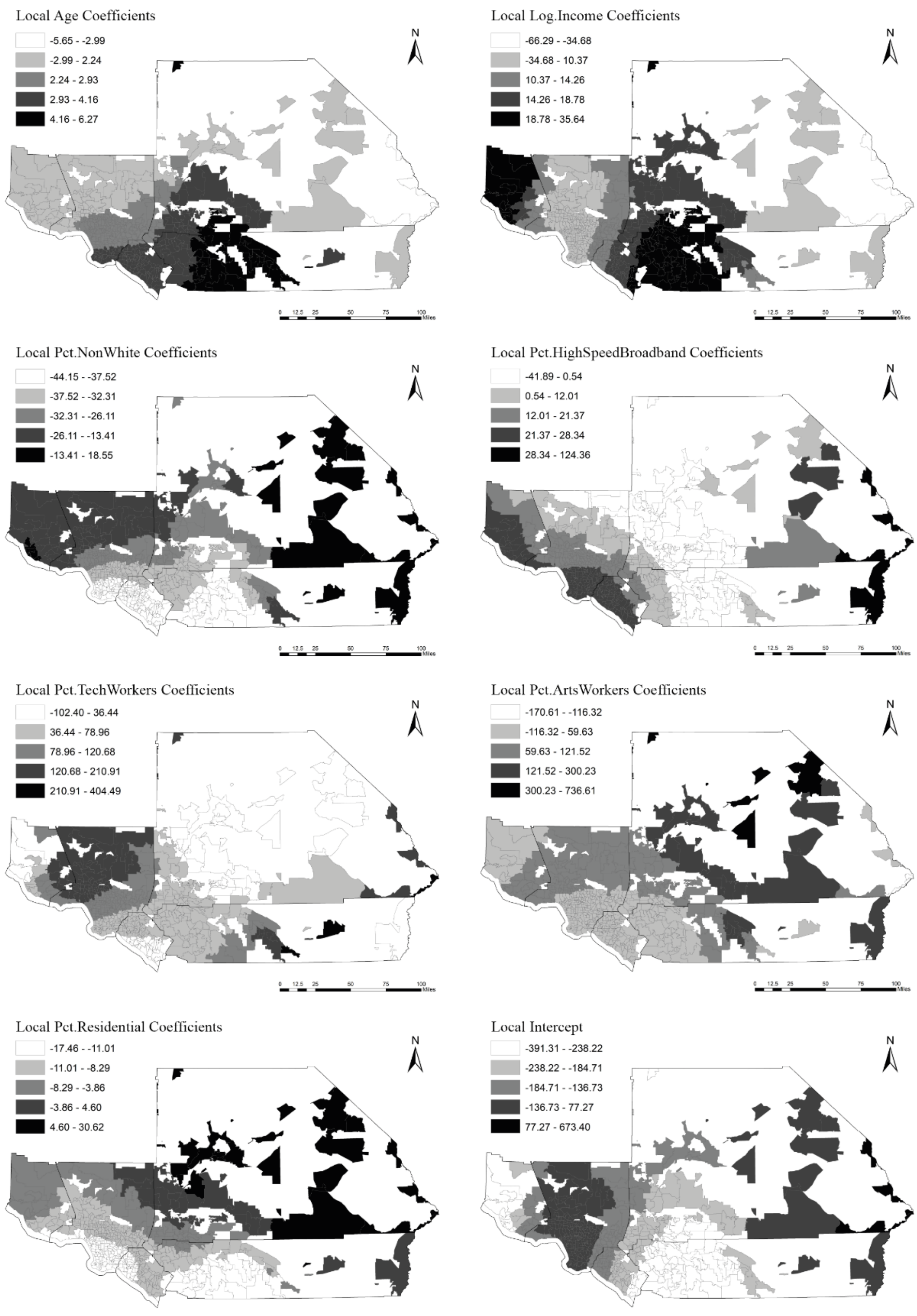

Figure 3.3 The spatial distribution of statistically significant GWR coefficients

3.5 Discussion and conclusion

Findings provide several insights into digital-age innovation adoption patterns using the case of civilian drones. First, the mapping of the adoption rate and the spatial regression models suggest that drone adoption is a geographically uneven process that is affected by the spatial dependence effect. Second, areas with early drone adoption are more likely to be economically well-off, have relatively more young adults, and have more workers in the technology and arts industries. This piece of finding is in part consistent with DeLaurentis's (2016) finding that economically well-off young adults favor the usage of drones than the general population. This study provides additional information about the racial and ethnic characteristics of early adopters. The drone adoption rates of the communities of color appear to lag when other factors are held constant. This finding can be a proxy to imply the constant racial and ethnic disparities in innovation adoption (e.g., Galperin et al., 2021). However, it does not necessarily mean drone adoption is either necessary or a good choice for all communities. Third, the availability of ICT infrastructure might increase the possibility of drone adoption. Moreover, innovation adoption is associated with land use and locational characteristics, and drone users might avoid areas with higher residential use in favor of coastal regions where scenic attractions are more concentrated. This finding is in part consistent with an early study by Lin Tan et al. (2021) that the acceptance of drone usage among residents was lowest in residential areas and highest in industrial areas. Based on these findings, this study suggests the following policy implications.

Although previous studies have explored various factors that are associated with the spatial clustering of innovation adoption, such as local social networks and the spatial heterogeneity of different explanatory factors (e.g., Mossberger et al., 2006; Van Dijk, 2003), this study advances this stream of literature by looking into the case of drone adoption. The spatial clustering of drones implies that the challenges of managing drone activity might also concentrate on certain areas. Therefore, this study suggests that drone regulation agencies (e.g., FAA, localities) should pay more attention to areas with significantly higher concentrations of drones (e.g., coastal regions).

The results also depict the demographic profile of areas with higher drone adoption rates as economically well-off and younger, while the drone adoption rates appear to lag for communities of color. These detections show the need for further research to investigate the socioeconomic circumstances that might be restricting the innovation adoption among populations of color. Barriers to innovation adoption have often been discussed as consumer perception, triability, and other market forces (e.g., Frambach & Schillewaert, 2002; Jensen, 1988), yet less is known about how cultural factors affect innovation adoption among certain groups of people.

While the digital divide's harmful impact on social equity has been extensively studied, our study contributes to the literature by suggesting that the digital divide might further magnified the growing inequality in the adoption of innovations. This has important implications for the access of historically marginalized communities (e.g., communities of color) to ICT technology, which is necessary to access information and/or operational infrastructure. Even though the low adoption rate of drones in communities of color can be considered as a proxy to measure innovation acceptance, this finding does not necessarily indicate that drone is either a necessity or a good option for these communities. As noted by other studies (e.g., Finn & Wright, 2012) communities of color are more cautious about drone surveillance. Therefore, considering the strong association between the presence of digital infrastructure and the drone adoption rate this study recommends planners and policymakers incentivize the provision of digital infrastructure to undersupplied areas, so as to lower the barriers to accessing such technology.

Admittedly, our study is not without limitations. While the study explored the dynamics related to the adoption of hobby drones, this study did not discuss the organizational behaviors related to the adoption of commercial and public safety drones. In the future, survey data that integrate qualitative factors such as public perception of drones, triability, and the effects of social networks would offer more insights regarding drone adoption patterns. It is still uncertain whether this association is caused by the historical distrust in surveillance technology among certain population groups. Future research on public/population groups' perception of drones is needed as both Chapters 2 and 3 indicate that the drone adoption is strongly correlated with racial and ethnic patterns.

Chapter 4. Managing Disruptive Technologies: Exploring the Patterns of Local Drone Policy Adoption in California

4.1 Introduction

The birth and growth of civilizations rely on technological innovations that shape and are shaped by civilizations (Mumford & Winner, 2010). Technological advancements and societal changes interact with each other in a dialectic fashion, and an important aspect in understanding this dialectic is how organizations respond to new technologies that can bring benefits or pose significant challenges to them (Orlikowski, 1992). Planners have long been involved in this process and will continue to be, as "every societal unit, from households, enterprises, institutions to governments, has always attempted to reduce uncertainty and mould its future to conform more closely to its aspirations since the beginnings of organised society" (Alexander, 1981, p. 134) through planning activities at various levels.

This study explores how local governments respond to the growing drone population and the associated challenges of managing their activities. Over the past decade, there has been a global proliferation of civilian unmanned aerial systems, more popularly known as drones. While drone activities for both recreational and commercial purposes are unevenly distributed across cities, this emerging technology is rapidly becoming part of our everyday lives. In January 2016, the Federal Aviation Administration (FAA) first announced that more than 300,000 drones are registered in its database (FAA, 2016a). As of February 2020, there were over 1.5 million registered drones in the United States, and more than 160,000 certified commercial drone operators (FAA, 2020).

On the one hand, drone technologies hold great promise in urban planning and policy-making; for instance, they are quickly becoming indispensable tools to collect "high-quality, accurate, and timely data to analyze sites and make data-driven decisions" (Stephens et al., 2020, p. 5). The low-cost, high-resolution, and real-time aerial surveying data collected by drones can be used for site analysis, mapping, 3D modeling, and visualization to support a range of urban planning activities, including transportation, environment, and disaster planning. The new technologies have also inspired policy makers to explore new ways to address chronic urban problems, such as traffic congestion and inefficiencies in service delivery, and realize the vision of smart(er) cities (Menouar et al., 2017).

On the other hand, as drone usage grows, so do safety, security, and privacy concerns about their operation (Gallacher, 2016). The safety concerns are particularly acute in areas near critical infrastructure with some incidents that attracted much attention, such as an alleged drone collision with an airplane at Heathrow airport (Wild et al., 2016) and sightings at Gatwick airport, which resulted in the suspension of operations that affected thousands of travelers in 2018 (O'Mally, 2019). Ready-to-fly drones, equipped with cameras and other sensors, have also intensified concerns about surveillance around the world, as they have become more affordable for both professional and recreational users.

In the United States, drone regulations have been implemented at all levels of government (Nelson & Gorichanaz, 2019). At the federal level, the FAA has been tasked with the design and implementation of laws and guidance for recreational and commercial drone users. Although both user groups are required to register their drones through the

FAA, they are subject to different restrictions. Recreational drone users are held to the Special Rule for Model Aircraft (Public Law 112-95, Sec. 336), which restricts the operation of drones at or below 400 feet above the ground in uncontrolled airspace. Meanwhile, commercial drone operators should fly in accordance with the Department of Transportation's Part 107 regulations implemented in August 2016 (FAA, 2016b). Part 107 of the regulations place additional and stricter restrictions on commercial drone operators who must obtain an FAA-certified drone pilot certificate before using drones for non-recreational purposes. A similar approach was undertaken by the U.K. Department of Transportation, with calls for further regulations and research by special interest groups such as the British Airline Pilots Association and International Air Transport Association ('Drone' hits British Airways Plane, 2016).

While federal regulations and guidelines play an important role in ensuring safety by preventing drones from interference with manned aircraft or flying over people and in certain locations, their effectiveness is limited in handling various concerns that arise in diverse places or circumstances. Moreover, the decentralized nature of drone activities and their operational characteristics (e.g., short-range, low-altitude, within visual line of sight) make it difficult for states and localities to simply rely on centralized interventions. Accordingly, by the end of 2019, 24 states passed privacy legislation, 10 states restricted drone access near critical facilities and infrastructure, and 19 states assembled committees or advisory boards for drone-related issues (National Conference of State Legislature, 2020). In the state of California, which has the largest number of registered drones and the largest number of drone incidents reported to the FAA, addressing the privacy and property disputes has been at the center of drone related regulations. In 2015, California passed the first paparazzi bill (AB 856) to prohibit drones from entering airspace above private property to capture images without permission. Attention has also been paid to managing drone activities in public spaces. For instance, the California Department of Parks prohibits the use of drones within state parks and it is a misdemeanor to interfere with the activities of first responders during an emergency.

Considerable efforts have also been made at the local level, which is the focus of this study. In the past few years, cities in California have seen a significant rise in drone-related incidents that interfered with first responders, damaging property, injuring people, and flying over critical infrastructure without permission (League of California Cities, 2017). To address these challenges and encourage appropriate drone use, some local governments have devised their own policies even before federal or state agencies began regulating drone activities. Recently, an increasing number of jurisdictions have also started to manage drone activities by providing more guidelines, such as local no-fly zones and specific law enforcement rules, apart from federal regulations. Yet, despite the significant role of local drone policies, our knowledge is limited about the (changing) patterns of drone policy adoption and the factors associated with such policy efforts at the local level.

This study examines the increase in local regulations on drone activities focusing, as an example, on cities in California. Specifically, it provides an investigation of whether and when cities have adopted their drone policies in relation to a range of city characteristics that can enhance or limit their ability to respond to technology-driven challenges according to relevant theories. Results show that both municipal capacity and motivation factors can significantly influence the local policy response and result in an uneven distribution of drone regulations. The distribution pattern revealed by this study also highlights the importance of support for communities in need and more systematic coordination between jurisdictions.

The remainder of this paper is organized as follows. The next section presents a review of the literature to understand what factors may contribute to local drone policy adoption and why. Following this, data collection and the methodology used are described. The last two present the results and discuss the findings and their broad implications.

4.2 Literature review

4.2.1 Recent development of drone policy studies

Over the past decade or so, the proliferation of drones has attracted increasing attention, and considerable scholarly efforts have been made to better understand how drone technologies can change the way our cities work. While some studies, such as Birtchnell and Gibson (2015) and Gallacher (2017), have shown a broad range of possible drone applications and the great promise drone technologies might hold for our urban research, teaching, and practice, others have identified challenges that could arise in adopting or deploying the new technologies in various contexts (see, e.g., Clarke, 2014; Wright, 2014). In particular, scholars have explored issues of safety, security, and privacy and stressed the importance of proper management of drone activities through regulation (see e.g., Clarke & Bennett Moses, 2014).

It is against this background that recent studies have started to examine regulatory principles, frameworks, or policies designed to prevent inappropriate use of drones. Policies specific to drone activities are available at all levels of government (Nelson & Gorichanaz, 2019). However, most existing studies on the management of drone activities have focused on national or state (or provincial) level regulations (see e.g., Brandon, 2017; Cracknell, 2017; Holden, 2014). For instance, through a comparative analysis of 35 countries in the Organization for Economic Co-operation and Development (OECD), Tsiamis et al. (2019) found that although all OECD countries had their own drone legislation, their frameworks varied considerably in defining and regulating drone activities. Finn and Wright (2012) contended that the current top-down regulatory frameworks in the U.S., U.K., and European Union could not adequately address privacy and other concerns related to the proliferation of drones. Similar findings have been reported by some state-level (or provincial level) studies, such as Brandon (2017) and Yao (2021), calling for a multi-layered mechanism that combines centralized governance and more active involvement of local governments in managing drone activities and associated challenges.

Another body of literature has paid close attention to the content of specific drone regulations and associated public discussions. Rao (2016) analyzed documents published between 2001 and 2015 by various stakeholders and found that federal drone regulations often lacked clarity on what drone users could do while overly emphasizing the risks involved. It has also been reported that drone regulations do not always reflect public concerns precisely. Specifically, although empirical evidence suggests that recreational users can pose a greater threat to both public safety and privacy, most federal regulations tend to aim at regulating commercial drone use (Finn & Wright, 2016). A thematic analysis of city council meetings in Southern California has shown that public concerns are likely to arise around issues of privacy, safety, and enforceability due to difficulties in building trust in the process of drone policymaking (Nelson & Gorichanaz, 2019).

Scholars have also conducted survey studies to understand public perceptions towards drone regulations. Through a nationwide survey in the United States, Kerry et al. (2014) found that most of the survey participants would support specialized regulations to limit drone uses. Wang et al.'s (2016) study further showed that the public believed that drone regulations should focus on two aspects: (1) drones' physical properties, such as size and lifting capacity, and (2) their operational properties, such as flying altitude and no-fly-zones. These studies commonly suggest that unrestricted use of drones is a major source of public concerns and local governments are at the forefront of adopting and enforcing drone policies. Furthermore, an increasing number of cities around the world have enacted drone specific regulations as part of their nuisance or airport ordinances (see e.g., Engberts & Gillissen, 2016; O'Malley, 2019). Therefore, the current landscape of drone policy literature urges researchers to systematically investigate how cities have adopted drone policies and factors behind the adoption patterns.

Although few studies have been conducted on drone policies at the local level, there is a rich body of literature that has examined what drives local governments to adopt other types of policies. Furthermore, it has been suggested that policy innovation is a complex, dynamic process in which various internal and external factors come into play (Araral, 2020; Hwang & Gray, 1991; Pitt, 2010). The development of new policies depends on an organization's "motivation to innovate [that can arise either internally or externally], the strength of obstacles against innovation, and the availability of resources" (Mohr, 1969, p. 111). The present study recognizes that the policy adoption process can be shaped by the following two groups of potential determinants: (1) motivation factors and (2) capacity factors. Specifically, the present study has considered multiple theoretical standpoints related to the adoption of local policies, such as interest group theory, strategic interaction theory, and social capital theory.

4.2.2 Drivers of local policy adoption

4.2.2.1 Motivation factors

Protection of public safety

Although government entities do not always work in tandem, they seek to address risks proactively and promote public interest by devising and implementing various initiatives and policies (Coglianese et al. 2003). The incentives behind these policies can be different, as Kingdon (2010) suggests: the policy making process can be a "policy stream" or a "problem stream" or a "political stream." Among others, the "problem stream" policies often concern pressing issues, for instance, protecting public health and safety in response to emerging challenges or disruptions that require public control (see e.g., Kent et al., 2017). Appropriate policy interventions can reduce public concerns about the potential risks and uncertainties brought by disruptive technologies and guide the development (or deployment) of new technologies (Nakamura & Kajikawa, 2018). In light of this, the emergence of drone activities and the associated potential risks may act as a primary motivator for policy actions because unregulated drone activities pose a significant threat to public safety and involve behavioral surveillance concerns (Clarke & Bennett-Moses, 2014). There have also been increasing public concerns over safety, privacy, and potential weaponization of drones in both private and public spaces (Clothier et al., 2015; Nelson et al., 2019; West et al., 2018). Exposure to these risks, however, can vary significantly across space and time. For example, in a global poll of 37 out of 44 nations, citizens opposed unrestricted drone use by governments (Pew Research Center, 2014). Similarly, Sakiyama et al. (2017) found that support for drone use varied by activity type. Furthermore, what matters most might not be the overall measurable risks (e.g., drone accidents per capita) but exposure to risks in public spaces where people gather frequently. Thus, cities may be more likely to adopt stricter drone regulations when they experience increased drone activity in public spaces (e.g., parks, beaches, and other recreational areas) and/or near important public facilities (e.g., airports).

Interest groups

Even though policy making involves broad public participation, interest group theory indicates that certain organized interest groups can have greater influence than the general public on stimulating policy actions (Dur & De Biere, 2007). This pluralist theoretical perspective suggests that, through inter-group competition, “the groups that do the best job of delivering political resources to local elected officials [are] most likely to see their preferred policies adopted” (Lubell et al., 2009, p. 297). For instance, Lewis and Neiman (2002) found that local growth management policies in California cities were highly correlated with homeownership, indicating the influence of organized interests of homeowners on growth management policy adoption. Many other studies, despite focusing on different policies, reported evidence of how local interest groups shaped the process of municipal policy adoption (see e.g., Shipan & Volden, 2008). It is important to note that the effects of coordinated action toward the provision of collective goods are more significant in small groups due to their greater coercive forces and individual incentives (Olson, 1971).

In the case of drone management, property owners with close access to drone attractors can form interest groups and urge local governments to take action to regulate drone activities. Meanwhile, there may be multiple interests at stake in the competition for policy attention thus leading to divided policy goals even within the same interest group (Browne, 1990). Drone users, as a potential interest group, may have a different view; however, their perspectives may depend on why and how they use drones. While both recreational and commercial drone users may oppose strict regulatory actions, commercial drone operators, who fly drones frequently for business purposes, may demand clear local guidance to avoid risks (Jones, 2017). In other words, the interests of some drone operators can be protected by local policies, particularly if the policies are implemented in a way that does not merely limit, but also manage, drone activities effectively.

Strategic interaction

Another source of motivation arises externally as local policy decisions can be significantly influenced by those of other local governments, especially that of localities nearby. In other words, "local governments … tend to act strategically and respond to what other (neighboring) jurisdictions do rather than making their … [policy] decisions independently" (Kim et al., 2020, p. 1). In his study on the dynamics of local growth control, Brueckner (1998) demonstrated this possibility and suggested that some cities adopted local (growth control) programs as a defensive strategy to protect themselves from spillovers from neighboring communities. Strategic interaction among local governments has also been reported in Nguyen (2009), Christafore and Leguizamon (2015), and other empirical studies. This interdependence among local governments can also be explained from the perspective of policy diffusion (Berry & Berry, 1999; Shipan & Volden, 2008). Policy makers can learn from neighboring localities through various channels of interaction, even though the role of geographic proximity in policy diffusion is not crystal clear (e.g., Mitchell, 2018; Shipan & Volden, 2012). Cities can simply replicate what neighboring cities do to manage drone activities through the transfer of knowledge among local politicians. Alternatively, when neighboring localities implement drone regulations, cities can foresee or be affected by potential spillovers, which may motivate them to enact a similar restrictive policy.

4.2.2.2 Capacity factors

Fiscal resources and law enforcement

Local policy development and implementation can sometimes be costly, and the fiscal health of a city may have a direct influence on the number and types of local policies it can implement (Lubell et al., 2009). Although adopting drone policies may not reduce tax revenues significantly, implementing these policies can lead to some expenditure, such as monitoring drone activities and training professional personnel to enforce the rules. Therefore, the fiscal capacity of a city may be a factor enabling the active adoption of drone policies. Another closely related capacity factor is the city's ability to implement law enforcement tasks. Studies have highlighted the association between law enforcement capacities and the adoption of public policies, suggesting that having a specialized agency would enhance the likelihood of relevant policy adoption (see e.g., Fleischmann et al., 1992; Steel & Lovrich, 1996). However, given the same level of per capita resources and law enforcement capacities, allocation of resources can be a complex process. Some small cities might act more swiftly than larger cities if they have fewer competing policy agendas. In contrast, small cities may have a limited ability to have dedicated personnel responsible for managing drone-related issues.

Government structure

While the motivation factors discussed above can trigger the initial process of policy formulation or deliberation, they do not necessarily lead to the adoption of formal policies under all circumstances. Equally important is the way a local government is organized to respond to various motivations. Local government structure can shape policy choices because professional public managers' perspectives and career interests may be different from that of elected officials (Feiock & Kim, 2001). Thus, government structure can affect the ability of interest groups to articulate their demands in the political arena and the willingness of local officials to impose preferred policies (Lubell et al., 2005). Empirical research has also shown that a mayor-council form of government can be more responsive to pressures for policy change than a council-manager system (see e.g., Fleischmann et al., 1992; Lee et al., 2014). In addition, the structure of regional governance (e.g., fragmented vs. consolidated) may also have a substantial influence on how individual localities behave (Kim & Jurey, 2013; Swanstrom, 2001).

Civic capacity

Another notable dimension of local capacity for policy development and adoption comes from outside of government. Participatory democracy and social capital theories suggest that citizen involvement has positive effects on democracy and that "citizens may increase their civic skills and become more competent if they participate in public decision-making" (Michels & De Graaf, 2010, p. 480). For instance, civic capacity (or human capital) has been considered important in various studies concerning sustainability policies, climate change policies, and technology adoption among local governments (see e.g., Sharp et al., 2010; Zahran et al., 2008; Zavattaro & Sementelli 2014). However, the definitions (and measurements) of civic capacity can vary. For instance, it may be defined as participants' ability to identify what can work for the common good or what should be the degree of engagement with public affairs (Saegert, 2006). Although civic capacity is a complex and latent variable, empirical studies have shown that the relationship between increasing civic capacity and educational attainment is robust (see e.g., Stone, 2001; Zavattaro & Sementelli, 2014). A key assumption made here is that population groups that are highly educated may engage in a higher degree of political activism and have greater capacity to support certain policy actions. This political activism and strong support, in turn, lead to a more effective democratic system in cities, which can deal with the emerging risks and challenges associated with drones or other (disruptive) technologies.

4.3 Data and Methodology

This study examines how 482 cities in California have responded to the proliferation of drones and identifies key determinants of drone policy adoption. This is accomplished through a review of municipal codes and multivariate survival analysis, as explained in detail below. The State of California currently has the largest population of drones and drone operators in the United States. In California, the number of total drone registrations more than quintupled from 37,000 to over 200,000 between 2015 and 2019. Recreational drones comprise a large portion of the total registrations, although commercial drone registrations have also seen a rapid increase (Figure 4.1). This increase could be attributed in part to the introduction of the FAA regulation that mandates drone registration prior to operation. Further, this upward trend in drone activities that has been seen in recent years is likely to continue in the future.

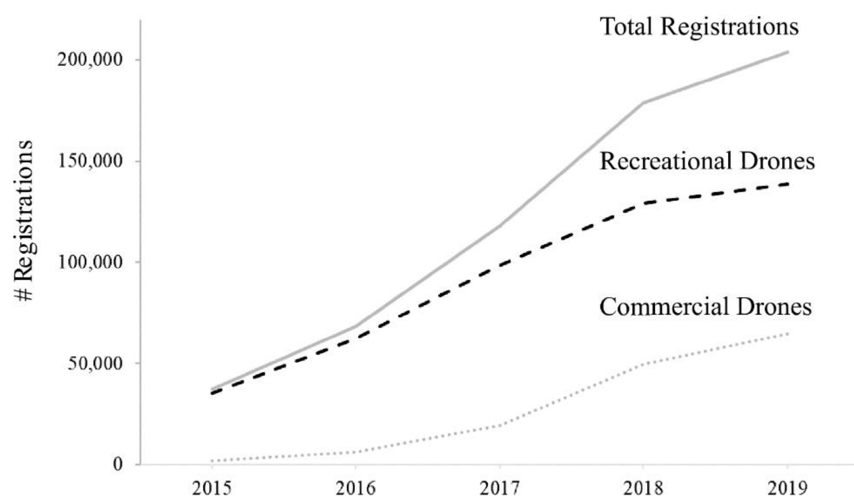

Figure 4.1 The number of registered drones in California, 2015-2019.

An important question is how individual cities in California have responded to the proliferation of drone activities and associated issues. This study reviews the municipal codes of 482 California cities to determine whether each city has adopted an ordinance to manage drone activities (1: yes, 0: no ordinance adopted), and if so, when (month/year).[1] Given that drone activities can be described in various ways, using a sample of cities, a pilot review of ordinances was conducted to develop an effective method of data collection for

[1] Ordinances passed by many cities in California are available at online municipal code libraries; this study used platforms such as https://codelibrary.amlegal.com, https://library.municode.com/, https://www.qcode.us/codes, and https://www.codebook.com/ (as well as city websites) for the ordinance review and data collection.

this dependent variable (i.e., the status of local drone policy adoption and the time of adoption). The following is a list of terminologies used to identify drone-related ordinances. The list was developed through an iterative process involving the preparation of an initial list and continuously updating the list throughout the ordinance review conducted between February- and March 2020:

- Drones
- Unmanned Aircraft/Aerial Systems (UASs)
- Unmanned Aircraft/Aerial Vehicles (UAVs)
- Micro Air/Aerial Vehicles (MAVs)
- Unmanned Air/Aerial crafts
- Model aircrafts
- Unmanned gliders
- Aircraft without a human aboard

For explanatory variables, consideration was given to a range of potential determinants that can represent both the motivation and capacity factors discussed in the literature review section. The motivation factors considered include the number of airports, percentage of population living within ½ miles of parks, beaches, open spaces, or coastlines, nearby cities' drone policy, and the numbers of registered drones and drone incidents. Cities with airports may regulate drone activities to ensure safety. For a similar reason, cities can be motivated to adopt their own ordinances when a large segment of residents live in close proximity to parks, beaches and other scenic areas. As discussed in the literature review, motivation can come from neighboring localities. In addition, the growing number of local drone registrations or drone incidents can stimulate local action. This study used the drone registration data from the FAA small Unmanned Aircraft System (sUAS) registration database. In aggregating the individual data records in the database to derive city-level counts a fuzzy string-matching tool (Cohen, 2020) was employed to address misspellings of city names.

To capture the influences of capacity factors, based on the literature review, the present study considered per capita city expenditures, law enforcement officers, and municipal form of government. Also included were city's population size, population density, and socio-demographic characteristics. Table 4.1 provides a detailed description of these variables and their data sources.

Table 4.1 Variables and data sources

Variables	Description	Data sources
Drone.Policy (DV)	1: Yes; 0: No	City websites and municipal code libraries[1]
Log.Population	Total population (logged)	Census[2]
Pop.Density	Population density in thousands per square mile	Census
Coastal.Cities	1: Coastal city; 0: non-coastal city	TIGER[3]
Airports	The number of airports within the jurisdiction	FAA.Airports[4]
Fiscal.Capacities	Per capita city expenditures (logged)	California State Controller's Office
Law.Enforcement	The number of law enforcement officers per capita	FBI
City.Governance	1: Charter city; 0: General law city	California State Controller's Office
Percent.High.Edu	Percentage of population aged 25 years and older with a bachelor's degree or higher	Census
Percent.Non-White	Percentage of non-White population	Census
Percent.Hispanic	Percentage of Hispanic population	Census

Nearby.Drone.Policy	Number of geographically adjacent cities that have adopted drone policy	City websites and municipal code libraries
PBOC.Access	Percentage of population within 1/2 miles of parks, beaches, open spaces, or coastlines	California Department of Public Health
Log.Comm.Drones	Number of registered commercial drones (logged)	FAA.UAS[5]
Log.Rec.Drones	Number of registered recreational drones (logged)	FAA.UAS
Log.Incidents	Number of drone sightings and incidents reported to FAA per thousand population (logged)	FAA.Sightings[6]

[1] Municipal code libraries: https://codelibrary.amlegal.com, https://library.municode.com/, https://www.qcode.us/codes, or https://www.codebook.com/

[2] Census 2000 and American Community Survey 5-year estimates (2011-2015).

[3] Census TIGER/Line and the U.S., Coastline National shapefiles

[4] FAA Airport Data and Information Portal

[5] FAA small Unmanned Aircraft System (sUAS) registration database

[6] FAA Unmanned Aircraft System (UAS) sighting reports

The study conducts a survival analysis to identify key factors underlying drone policy adoption at the local level. Survival analysis, also known as time-ti-event analysis, has been widely used to model the probability that an event would occur as a function of time and other variables. Specifically, the study employs the Cox proportional hazard model (Cox & Oakes, 1984). The Cox proportional hazard model is expressed as follows:

$$h_i(t) = h_0(t) \cdot \exp\,(\beta X)$$

where $h_i(t)$ is the proportional hazard function of adopting a drone policy for city i in month t; $h_0(t)$ refers to the baseline hazard; and βX is the matrix of estimable parameters and covariates. The model assumes that a city's policy adoption rate (hazard rate) is proportional to the baseline hazard, and the ratio is an exponential function of the explanatory variables. In addition, the Cox proportional hazard model is often preferable to logit or probit modeling approaches, since it avoids the need to parameterize the baseline hazard function (Jones & Branton, 2005; Wang, 2012).

The survival analysis was conducted in the following two ways: (1) long-term analysis (2002-2019) and (2) short-term analysis (2015-2019), in part owing to the limited data availability for some of the explanatory variables in early years. The long-term analysis was designed to examine the dynamics of local drone policy adoption from 2002 to 2019 using the variables for which data were available in or near the baseline year (2002). The second analysis, to gain further insights with additional explanatory variables, focused on a shorter period (2015-2019) during which many cities adopted their drone policies. In the latter analysis, given the time horizon (2015-2019), cities that had adopted local drone policies before 2015 were excluded. However, these cities were used to construct a variable (*Nearby.Drone.Policy*) indicating how many adjacent cities had already adopted drone policies as of the base year and thus enabled testing of the presence of strategic interaction among local governments. The Cox-proportional hazards model was estimated by maximum likelihood in Stata 14.

4.4. Results

4.4.1 Spatio-temporal patterns of local drone policy adoption

Over the last two decades, approximately 20% of cities in California have adopted their own drone policies. The City of Laguna Niguel, an affluent coastal municipality in Orange County, first adopted its drone ordinance in December 2002 to prohibit the flying of electric- or gasoline-powered model aircraft at the city parks (Laguna Niguel Code of

Ordinances, Sec. 13-1-81), and this early adoption was triggered by a series of local drone accidents at that time (*Los Angeles Times*, 2002). Some other cities, which also experienced similar nuisance caused by model aircraft, such as Costa Mesa and Carlsbad, also added drone ordinances to their municipal codes in the early years when federal- or state-level guidance was scarce. The municipal code review shows that these early adopters tended to have simple ordinances with limited details that prohibited the flying of model aircraft in designated public spaces; however, recent adopters have included greater flexibility and elaborated more on allowable drone activities (e.g., flying with permits, maximum altitude, etc.) instead of simply prohibiting all drone use in broadly defined areas.

The adoption rate of local drone ordinances, however, remained low until the early 2010s. As shown in Figure 4.2, 2015 was when many cities began adopting drone policies, and the increasing trend peaked in 2017 although it has slightly decelerated in the past few years. During this period, both federal and state governments have taken actions to regulate drone operations. In December 2015, for instance, the FAA introduced rules requiring owners of small drones to register their devices and attach registration codes to the flying objects. In June 2016, the FAA also released Part 107, which requires individuals to obtain a "Remote Pilot Certificate" if they want to fly their drones for commercial purposes. At the state level, AB 856 and AB 1680 were passed in 2015 and 2016, respectively, to prohibit drone operators from entering the airspace above the land belonging to another person without consent and from interfering with first responders during emergencies. The increased adoption of local drone policies in California may probably be associated with such increased regulatory activities or resources at the federal and state levels during this period of time. It is important to stress that more recently adopted ordinances tended to provide more detailed guidance for drone activities. The City of Los Angeles, for instance, implemented more elaborated rules on drone operations by expanding the definition of drones and specifying when (e.g., daytime only), where (e.g., below 400 feet and stay away from airports), and how (e.g., within visual line of sight, vision enhancing devices are not allowed) drones should be operated within the city. The evolving patterns of drone ordinances may suggest a learning process that would have enabled cities to be more adaptable to changes induced by disruptive technologies. Some examples of these local drone ordinances are presented in Appendix A.

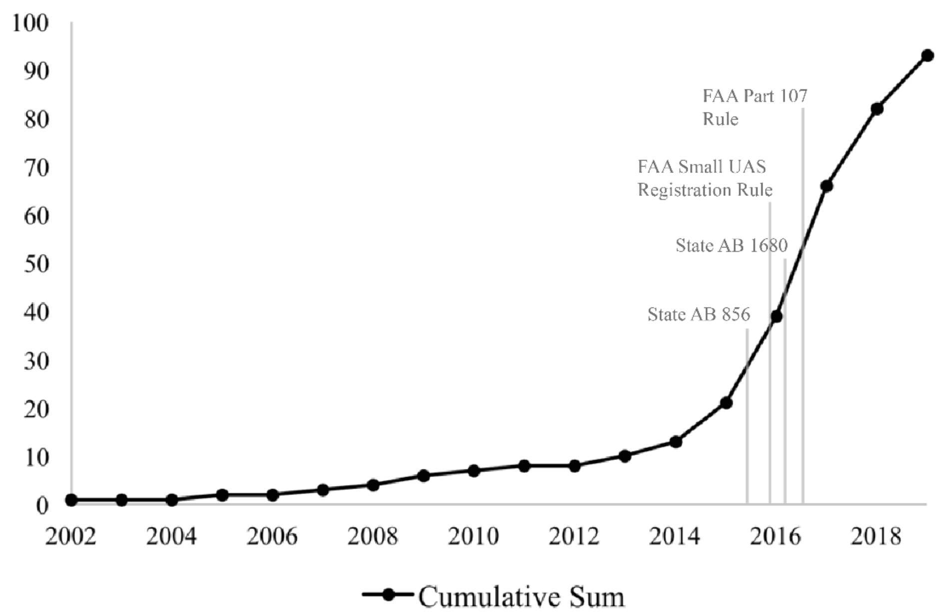

Figure 4.2 Local drone policy adoption trend in California, 2002–2019.

While approximately 20% of the cities in California have adopted their own policies for managing drone activities, the spatial distribution of such cities is far from uniform. Furthermore, the spatial pattern of the policy adoption has changed over time. Figure 4.3 illustrates the evolving spatial pattern by showing places with local drone policies at four different times. During the early adoption phase from 2002 to 2013, drone policy adopters were mostly coastal cities in Southern California. From 2013 to 2015, the policy adoption steadily diffused into inland cities, but still clustered in Southern California. From 2015 to 2017, this policy diffusion was further accelerated in Southern California, and this period witnessed the emergence of local drone policy adopters in Northern California. In the last period (2017-2019), the adoption rate grew gradually without a significant shift in spatial distribution.

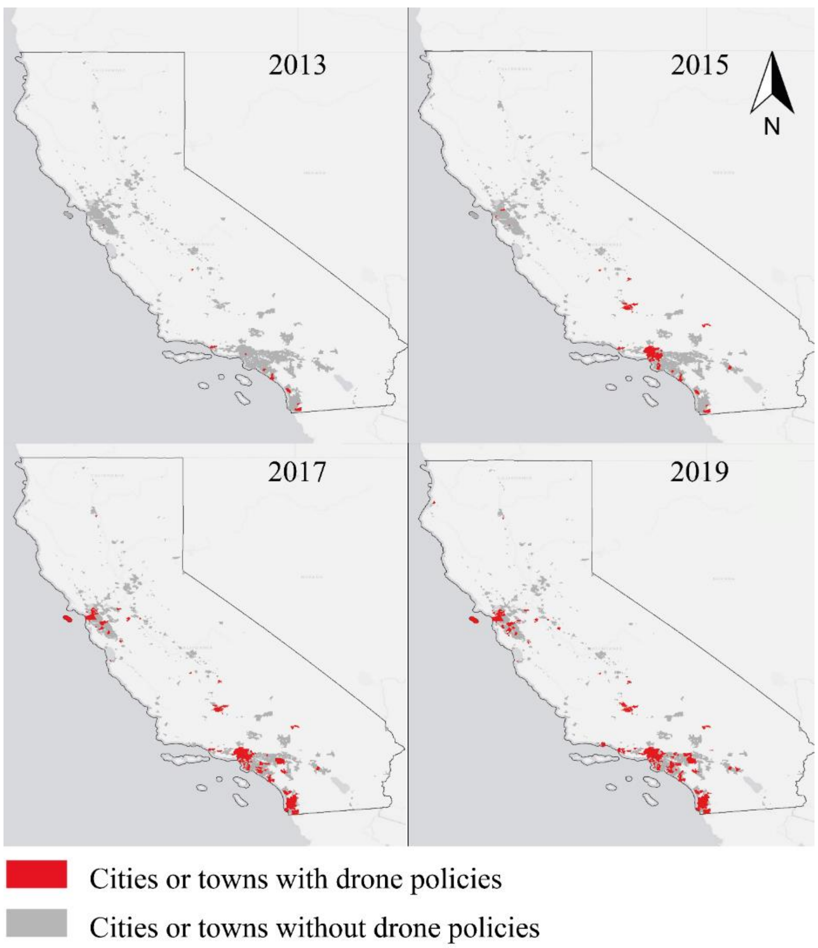

Figure 4.3 Spatial distribution of local drone policy adoption.

4.4.2 Drivers and constraints of local drone policy adoption

As noted in the previous section, this study used survival analysis to examine what drives (or constrains) the adoption of drone policies at the local level. The Cox proportional hazard model was estimated for two distinct time horizons: long-term (2002-2019) and short-term (2015-2019). Table 4.2 presents the analysis results including those from the long-term policy adoption model and two versions of the short-term model. The first version of the short-term analysis employed the same set of explanatory variables as in the long-term analysis, while the second version used an expanded list of predictors. The two versions together are expected to provide a more nuanced understanding of the determinants of the policy adoption dynamics. Logistic regression was also conducted to check whether an alternative method would alter the results significantly. The findings from these two approaches were found to be largely consistent with one another (see Appendix B).

Table 4.2 Survival analysis results

	Long-term (*N* = 474)	Short-term (*N* = 465)	
		Basic model	Full model
Log.Population	0.513 ***	0.403 **	0.343 *
	(0.129)	(0.141)	(0.165)
Pop.Density	0.140 ***	0.184 ***	0.118 **
	(0.027)	(0.031)	(0.040)
Coastal.Cities	0.558 *	0.480	0.081
	(0.247)	(0.278)	(0.293)
Airports	0.007	0.082 *	0.092 *
	(0.009)	(0.036)	(0.037)
Fiscal.Capacities	0.136	0.135	-0.100
	(0.108)	(0.214)	(0.227)
Law.Enforcement	-3.880	-4.309	-2.381

	(9.906)	(10.591)	(7.686)
City.Governance	-0.191	0.583	-0.772
	(0.263)	(0.328)	(0.327)
Percent.High.Edu	1.613 **	2.521 **	0.959
	(0.823)	(0.978)	(1.086)
Percent.Non.White	-2.095 *	-1.557 *	-1.421 *
	(0.899)	(0.760)	(0.617)
Percent.Hispanic	-1.414 *	-1.229	-0.325
	(0.697)	(0.644)	(0.262)
Nearby.DronePolicy			0.247 *
			(0.103)
PBOC.Access			0.027 ***
			(0.007)
Log.Comm.Drones			0.021
			(0.032)
Log.Rec.Drones			0.194
			(0. 194)
Log.Incidents			0.037 *
			(0.016)
Log likelihood	-508.629	-417.526	-409.759
AIC	1037.258	855.051	841.518
BIC	1078.870	896.472	903.649
$P > \chi^2$	0.000	0.000	0.000

Notes: Standard errors are in parentheses. The estimated coefficients show the change in the expected log of the hazard ratio due to a one-unit change in each variable, holding all other predictors constant. * Significance level of 0.05, ** Significance level of 0.01, *** Significance level of 0.001.

First, the long-term analysis showed that population size (*Log.Population*) has a significant positive impact on the adoption of local drone policies, which is consistent with the literature suggesting that an increase in city size can lead to a higher probability of policy adoption (Krause, 2011). Similarly, population density (*Pop.Density*) exhibited a significant positive coefficient, indicating that dense cities were more likely to adopt drone policies early, all other things being equal. Cities with higher densities may have a greater need to regulate drone activities. Alternatively, such cities might also have an environment in which residents can share their concerns (and relevant information) with each other and form interest groups for policy adoption more actively, as information flow scales with population density (Pan et al., 2013).

In addition, the results indicated that coastal cities (*Coastal.Cities*) were more inclined to adopt city ordinances to manage drone activities. More specifically, the coefficient (+0.558) implies that the rate of drone policy adoption is about 75% higher in coastal cities than in non-coastal cities. This finding is consistent with what was shown in Figure 4.3 (i.e., a higher probability to have local drone ordinances in coastal cities). The *Airports* variable also showed a positive coefficient perhaps because the presence of airports can urge cities to regulate drone activities. In this case, however, the positive coefficient was not statistically significant.

Fiscal capacity (*Fiscal.Capacities*) and law enforcement capacity (*Law.Enforcement*) variables showed insignificant effects. suggesting that the lack of per capita fiscal and law enforcement capacities may not have been a significant barrier to the adoption of local drone policies in the state over the last two decades. It should be noted that the aggregated capacity of a city might have been captured by the city's population size, which turned out to be a significant predictor. In the long-term analysis, the governance form variable (*City.Governance*) also showed no significant influence, indicating that there was no systematic difference between charter cities and general law cities. This piece of evidence may enrich the debate on to what extent the government form matters in predicting policy adoption, as previous studies have produced mixed results (see e.g., Nelson & Svara, 2012; West & Berman, 1997;).

However, the percentage of highly educated individuals (*Percent.High.Edu*) was found to be a significant predictor of policy adoption. It is important to note that cities with higher percentages of non-White (*Percent.Non.White*) or Hispanic (*Percent.Hispanic*) populations were less likely to adopt drone ordinances, all other factors held constant. While cities with drone ordinances only had 30.2% non-White residents on average, cities without such regulations had 34.0% in California. This finding may indicate the relatively lagged adoption of local drone policies in communities of color, which could make their residents more vulnerable to the potential risks posed by proliferating drone activities. However, it is beyond the scope of this study to evaluate whether the absence of local drone ordinances is problematic or not from a normative perspective.

The short-term model estimation results were generally consistent with those of the long-term analysis. Both population size and population density showed significant positive effects on the policy adoption for a shorter period of time (2015-2019), as found in the long-term model. When the same set of explanatory variables was used (i.e., the second column of Table 4.2), the positive effect of the percentage of highly educated individuals was found to be significant, while the non-White population showed a significant negative association as in the long-term analysis. Again, the per capita fiscal capacity and law enforcement capacity variables showed no significant effects.

There are, however, some notable differences between the long-term and short-term analysis results. In the case of the short-term analysis focusing on 2015-2019, coastal cities no longer showed a significant difference, reflecting the noticeable policy expansion into inland areas in these recent years, as shown in Figure 4.3. Instead, the airport variable gained significance, indicating the increased importance of airports in explaining the adoption of local drone policies in recent years. Furthermore, unlike the long-term analysis, the influence of the percentage of Hispanics became insignificant, while still exhibiting negative coefficients.

More importantly, the presence of drone policies in geographically adjacent cities (*Nearby.Drone.Policy)*, a newly included variable (see the third column of Table 4.2), showed a significant positive association with drone policy adoption. The probability of local drone policy adoption was found to increase by about 28% in response to an additional neighbor with drone policies. This finding deserves attention, as it suggests the importance of strategic interaction among local governments, which can be explained in two possible ways: 1) the presence of spillovers (i.e., if regulated in a city, drone activities may spillover to adjacent cities) as a significant motivator of local (regulatory) policy adoption or 2) the spatial nature of policy diffusion or learning processes.

According to the short-term analysis, another significant predictor was the percentage of population with good access to parks, beaches, open spaces, or coastlines (*PBOC.Access*). This variable had a significant, positive effect, suggesting that localities with or in proximity to these potential attractors tended to adopt local regulations to protect public safety. The potential motivation (or risk) factor, measured in terms of the log of the number of drone incidents per thousand people (*Log.Incidents*), also showed a significant positive relationship with the dependent variable, suggesting that the policy action can be driven by such immediate motivations.

4.5. Conclusion and Discussion

4.5.1 Conclusion

While the contribution of federal and state legislation should not be underestimated, local drone policies are becoming a critical part of the effort to manage the rapid proliferation of civilian drones and address growing public concerns over unregulated drone activities. This study sought to provide a deeper understanding of the increasingly important dynamics of local drone policy adoption and the key determinants affecting the policy adoption process. To do so, the evolving patterns of local drone policy adoption in the state of California during 2002-2019 were examined by reviewing municipal ordinances and conducting survival analysis.

The evidence presented in this study suggests that both motivation and capacity factors play an important role in shaping the dynamics of drone policy adoption at the local level. In California, approximately one-fifth of the incorporated cities/towns had their own policies (municipal codes) to manage drone activities in their jurisdictional boundaries. Coastal cities were found to adopt local drone policies early, while cities with airports and higher percentage of population living close to open spaces have shown a higher rate of policy adoption in more recent years, suggesting that the presence of drone attractors and public facilities to be protected might motivate localities to adopt regulatory measures in a more active manner. Both population size and population density were also significantly associated with policy adoption, and a similar pattern of (positive) association was detected for the level of educational attainment, as expected. One important finding was the spatial clustering of the local policy adoption. The clustering pattern may indicate the presence of strategic interaction among local governments, and the survival analysis confirmed this association suggesting that a city's policy adoption is not independent on what neighboring jurisdictions do. It should also be stressed that drone policy adoption among communities of color appears to lag behind that of other cities.

4.5.2 Discussion

Overall, these findings provide an opportunity to better understand the complexity of local drone policy adoption. The challenges of managing autonomous agents in urban settings urge planners and policy makers to rethink regulatory strategies from a holistic yet practical perspective (Rowling & Blauwkamp, 2021). Rapid diffusion of drone technologies across numerous industrial sectors, user groups, and regions requires both federal/state-level legislation and collaborative local policies rather than simply relying on a single approach. It is important to consider the uniqueness of each nation or region in coordinating efforts vertically and horizontally.

As shown in this study, local governments have been at the forefront of handling new urban challenges even before the implementation of state or federal regulations. The literature on policy dynamics shows that policies can emerge from local governments to states in addressing various issues, such as smoking bans, climate change mitigation, and smart city governance (see e.g., Breuer et al., 2014; Lutsey & Sperling, 2008; Shipan & Volden, 2006). This study suggests that similar bottom-up policy diffusion patterns might exist in managing emerging technologies by showing the relatively earlier adoption of municipal drone ordinances by some cities. The lessons from pioneers like these localities in California can also be transferred broadly to other cities around the world, as suggested by Custers (2017) and Jones (2017). A network of global cities or policy makers can play a significant role in facilitating such a process of policy and knowledge transfer.

The local policy adoption pattern and its association with socio-demographics also deserve special attention. While local drone policies have been increasingly adopted in California, cities with a high percentage of people of color showed a slower rate of policy adoption. This variation in local policy responsiveness to technology-driven challenges and opportunities is not unique to California. The uneven distribution can emerge in various forms in other states and countries, and this issue can be mitigated by providing additional assistance to those communities in need and by facilitating horizontal collaborations among localities, which could be a long-term strategy to empower cities to address various challenges emerging both now and in the future (Honadle, 1981; Leon-Moreta et al., 2020).

The spatial clustering of local drone policy adoption seems to further highlight the importance of collaboration among cities. The clustered pattern detected here is consistent with the findings of other studies on local land use policies, such as growth control and green space provision (see e.g., Brueckner, 1998; Chen et al., 2017). Recent studies on shared autonomous vehicles (SAV) also suggest that parking demand is likely to be displaced from downtown to nearby poor neighborhoods without coordinated regional policies for SAV (see e.g., Zhang & Guhathakurta, 2017). In other words, it is important to explore ways to collaboratively manage new technology-driven challenges, while discouraging NIMBYism. In promoting collaboration, careful consideration should also be given to the existing institutional arrangement and other socio-political issues in each nation.

Finally, local drone policy shares many characteristics with cell tower siting policy in terms of policy issues and adoption patterns. Both civilian drone and cell tower have gone through a period of exponential growth that triggers public concerns towards the safety and security of the technology (FAA, 2020; Waring, 2017). Then all levels of government response to the public concerns with various regulatory interventions. Similar to the claims that drone activities are posing risks to private property, a review of local cases related to cell tower siting disputes suggests that in California, visual pollution is a legitimate concern in siting procedures and property value framing is sometimes found in local authorities' framings of a cell siting (de Graaff & Bröer, 2019). Moreover, early studies suggest that local governments are leading the regulatory efforts to mitigate the potential risks of both cell towers (Broer, de Graaff, Duyvendak and Wester, 2016). These emerging overlaps in managing technology in localities deserve more scholarly attention.

Admittedly, the present study is not without limitations. Although explicit attention was paid to the timing of each city's drone policy adoption, this research did not discern qualitative differences among local drone ordinances in the survival analysis. Future research may examine variations in the content and structure of local drone policies to provide deeper insights into the mechanisms of local policy making processes. Furthermore, the promising potential of this emerging technology, as well as the challenges it poses, deserves more attention. Exploring ways to leverage this new tool to improve planning practice and address chronic urban issues, as done by a recent American Planning Association's Advisory Service report (Stephens et al., 2020), is undoubtedly an important agenda. In doing so, planners should recognize that civilian drones, or urban aerial mobility (UAM) technologies, are likely to continue evolving through constant interactions with societal changes based on how we encourage their positive development/deployment while simultaneously curbing the risks posed by these autonomous and unmanned systems in the sky.

Chapter 5. A Scenario Analysis of Supply-side Opportunities of Urban Air Mobility in Southern California

5.1 Introduction

The transportation sector faces the challenge of meeting the growing demand for convenient passenger mobility while reducing congestion, improving safety, and mitigating emissions. Automated driving and electric propulsion are disruptive technologies that may contribute to these goals, but they are still limited by congestion on existing roadways and land-use constraints. Urban Air Mobility (UAM) can positively contribute to a multimodal mobility system by leveraging the sky to better link people to cities and regions. UAM technologies and concepts have been searched and developed by industry, academia, and government for decades. Commercial UAM operations have begun in the United States since at least the 1940s. For example, from 1947 to 1971, Los Angeles Airways used helicopters to transport people and mail between dozens of locations in the Los Angeles basin, including Disneyland and Los Angeles International Airport. During the same era, from 1949 to 1979, the New York Airways primarily used helicopters to fly people between helipads in Manhattan and airports in the New York area such as LaGuardia, JFK, and Newark. Tragically, these initial commercial experiments experienced several fatal accidents and after those accidents, the once-booming operation of helicopter-based UAM was halted nationwide, and the resulting financial difficulties led these companies to cease operations (McFadden, 1977). Despite these historical operation failures, recent technological advances provide an opportunity for the resurgence of urban air mobility.

According to NASA (Thipphavong et al, 2018), the electric vertical takeoff and landing (eVTOL) UAM system has reached "a level of maturity to enable UAM using safe, quiet, and efficient unmanned vehicles to conduct on-demand and scheduled operations (p.1)." Types of UAM operations could be emergency responses, humanitarian missions, newsgathering, package delivery, and passenger transport. Among all types of potential applications, the use of passenger transport is of the greatest attention given its promising future to alleviate traffic congestion with green technology from a new dimension. For instance, a study in Bay Area has provided evidence that a potential eVTOL UAM system would have a significant impact to reduce the trip time for trips greater than 15 miles (Antcliff, Moore, and Goodrich, 2016). And fully loaded eVTOL's greenhouse gas emissions per passenger-kilometer are less than half than internal combustion engine vehicles and 6% lower than ground electric vehicle (Kasliwal et al., 2019).

Despite the technological advances and growing commercial interest, it is important to note that the adoption of UAM still faces multiple challenges as highlighted by many researchers. Such challenges include estimating the demand for air taxi services (transportation modeling and market analysis), air traffic control, operation, infrastructure planning, safety, and regulations (e.g., Booz, 2018; Hasan, 2019; Johnson et al., 2018; Pradeep and Wei, 2018; Rajendran and Zack, 2019; Sun et al., 2018; Thipphavong et al., 2018). Another important issue for scaling UAM in built-out metropolitan regions is identifying appropriate landing sites along with other supply-side opportunities and constraints, such as no-fly zones, noise levels, and school zones, to accommodate the regional wide deployment of eVTOLs.

To identify the supply-side opportunities and assess the impact of spatial constraints on these opportunities, this study 1) explores the availability and spatial distribution of current urban infrastructure that can be potentially used as UAM landing sites or vertiports; 2) conducts scenario analyses on how various spatial constraints affect the supply-side opportunities of UAM; 3) investigate the how different scenarios affect the accessibility of vertiports for different groups of home-workplace commuters.

The paper proceeds as follows. Section 2 presents the literature review. Section 3 describes the data collection process and scenario analysis framework. Section 4 presents the results of the scenario analysis. And Section 5 discusses the conclusion, implications, and limitations of the study.

5. 2. Literature review

Although Urban Air Mobility (UAM) is an emerging mode of transportation, many studies have been conducted to understand the factors associated with transportation technology acceptance. In particular, the social acceptance and user perceptions of ground autonomous vehicles (GAV) have received increasing scholarly attention in recent years. In the case of UAM, examining recurring factors in relevant studies of ground autonomous vehicles and traditional aerial services (e.g., on-demand aerial service) provide useful insights given as only a few pioneering studies have focused on users' preference of UAM.

5.2.1 Demand-side factors associated with UAM or GAV adoption

Increasing scholarly and institutional attention has been paid to understanding factors associated with the adoption of autonomous transportation technologies. In recent years, social barriers and key factors associated with user adoption have been widely studied for ground autonomous vehicles. Sociodemographic factors, such as income level and gender, were found to be significantly associated with autonomous vehicle acceptance

(Bansal et al., 2016; Hohenberger et al., 2016). Higher-income, technology-savvy males, who live in urban areas, and those who have experienced more car accidents (risk takers) have a greater interest in and higher willingness to pay for GAV (Bansal et al., 2016). User choice is also influenced by social networks including neighbors and close friends. Kyriakidis et al. (2015) pointed out that the adoption of ground GAV is hindered by users' perception of risks (e.g., data privacy, remote hacking). While trust is the most critical factor related to GAV acceptance, perceived ease of use and perceived usefulness are also significantly related to innovation adoption (Zhang et al., 2019). While GAV holds the promise of reducing the number of crashes and fatalities on the roads, safety concern is one of the major barriers to promote the adoption of GAV (Moody et al., 2020).

Interestingly, these concerns about GAV adoption are reappearing in early studies on UAM adoption. In a stated preference survey study in Germany, Al Haddad et al. (2020) explored user perception on UAM. The study indicated that safety and trust are prior concerns for UAM adoption and adopters are younger and have higher income. Fu et al. (2019) extended the study in Munich, Germany, and their results further suggested that younger individuals, as well as the older populations with higher household income, are more likely to adopt UAM. Also, trip purpose proved to be a significant consideration, with non-commuting travel being the respondents' most preferred GAV option. Airbus's survey (2019) in four different countries reported that communities are most concerned about safety, followed by the type of sound generated from the aircraft, and then the volume of sound from the aircraft. Less than half (44%) of all respondents' initial reactions to UAM are in support or strong support while 41% of all respondents believe UAM is either safe or very safe. Deloitte (2019) reinforced that demographic factors are significantly associated with UAM adoption as younger generations (Gen Y and Gen Z) are more likely to agree that UAM provides for an efficient alternative mode of urban transportation. Table 5.1 presents a summary of recent studies on factors associated with UAM or AV adoption.

Table 5.1 Recent demand-side key studies on UAM adoption

Authors	**Year of publication**	**Area of research**	**Study area**	**Key findings**
Al Haddad et al.	2020	UAM	Germany	1) Safety and trust, affinity to automation, data concerns, social attitude, and socio-demographics are important issues for UAM adoption; 2) Skeptical respondents had behavior similar to late and non-adopters.
Bansal et al.	2016	GAV	Austin, Texas	1) Higher-income, technology-savvy males, who live in urban areas, and those who have experienced more crashes have a greater interest in and higher willingness to pay for AV; 2) User choice is dependent on friends' and neighbors' adoption rates.
Fu et al.	2019	UAM	Munich, Germany	1) Travel cost, and safety may be critical determinants in UAM adoption; 2) younger individuals, as well as older individuals with high household income, are more likely to adopt UAM; 3) during the market entry stage, potential travelers may favor UAM particularly for performing non-commuting (recreational flying) trips.
Garrow et al.	2018	UAM	U.S. (CSAs)	Study in progress
Hohenberger et al.	2016	GAV	Germany	1) The anxiety level has a significant gender-related difference towards AV adoption; 2) differential effect of sex on anxiety was more pronounced among relatively young respondents and decreased with participants' age.
Kyriakidis et al.	2015	GAV	109 countries	1) Most people think manual driving is still the most enjoyable mode of travel; 2) Respondents were found to be most concerned about software hacking/misuse and were also concerned about legal issues and safety; 3) Respondents from more developed countries were less comfortable with their vehicle transmitting data.
Lidynia et al.	2016	Drones	Aachen University, Germany	1) Laypeople feared the violation of their privacy whereas active drone pilots saw more of a risk in possible accidents; 2) participants had clear expectations regarding

				the routes drones should and should not be allowed to use.
Lineberger et al. (Deloitte)	2019	UAM	20 countries	1) Despite the substantial progress made in terms of vehicle design and technology, consumers continue to doubt the safety of UAM; 2) regional and generational differences play a critical role in the perceived UAM safety; 3) 49% of respondents in the United States were unconvinced about UAM safety, while only 39% are skeptical about safety in China; 4) younger consumers surveyed (Gen Y and Gen Z) agree that UAM provides for an efficient alternative mode of urban transportation but are more apprehensive about its safety.
Peeta et al.	2008	On demand air service (ODAS)	Indiana, Illinois, and Florida	1) Travel distance, service fare, and the ODAS location are key factors influencing user switching decisions (from traditional air service to ODAS); 2) ODAS landing location is a key determinant of its operational viability, and has significant implications for policy-makers, regional/city planners, operators, and businesses; 3) While ODAS proximity to work is an attractive attribute for users, environmental concerns can arise if close to residential areas.
Yedavalli et al. (Airbus)	2019	UAM	Los Angeles, Mexico City, New Zealand, and Switzerland	1) Communities are most concerned about safety, followed by the type of sound generated from the aircraft, and then the volume of sound from the aircraft; 2) Other concerns include the time of day at which aircraft are flown and the altitude at which aircraft fly; 3) 44.5% of all respondents' initial reactions to UAM is in support or strong support while 41.4% of all respondents believe UAM is either safe or very safe.
Zhang et al.	2019	GAV	China	1) Trust was the most critical factor in promoting AV acceptance; 2) Perceived ease of use (PEOU) and perceived usefulness (PU) were significant factors; 3) The effects of PEOU and PU were weaker compared to trust.

5.2.2 Supply-side factors related to UAM adoption

While demand-side factors have attracted lots of scholarly attention in early studies on UAM, the identification of viable UAM landing sites and other supply-side constraints/opportunities are pre-conditions to advance the empirical studies on UAM adoption (see Figure 5.1 for various archetypes of UAM landing sites). Vascik and Hansman (2017) and Fadil (2019) suggested that vertiports can leverage the underutilized urban infrastructures such as helicopter pads, barges over water, inside highway cloverleaf, and qualified rooftops (e.g., parking structures), with the constraints of other supply-side factors such as air space zones, land use regulations, and population density. These findings coincide with Early studies (e.g., Peeta et al., 2008) on on-demand aerial service (ODAS), which suggested that landing location is a key determinant of its operational viability. While ODAS's proximity to work is an attractive attribute for users, environmental concerns can arise if it is close to residential areas. Fadil (2019) also emphasized that median income distribution, land value, and job density should be considered in the placement of UAM landing sites. Rath and Chow (2019) identified another research trajectory in which the locations of UAM vertiports served as a transition mode for airports between long-distance air travel and short/ medium distance air travel. In his work, vertiport placement was optimized based on airport traveler data. Moreover, the operational capacities of ground infrastructure (supply-side) play an important role to improve the operation efficiency of UAM systems. Vascik and Hansman (2017) suggest that balancing the number of gates and the number of vehicles will maximize the utility of UAM mode when vehicle specifications are held constant.

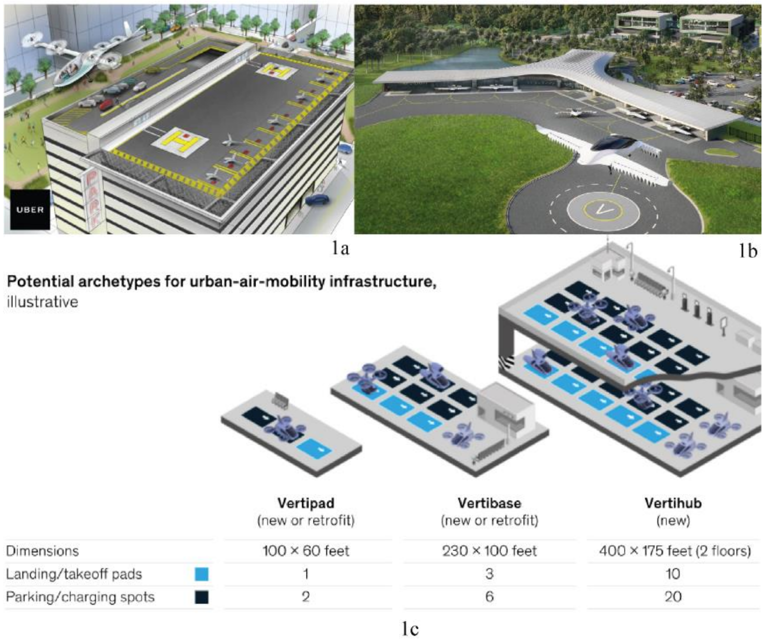

Figure 5.1 Examples of UAM landing sites. 1a. UAM landing site design by repurposing underutilized parking structure rooftops (Uber, NASA). 1b. UAM vertiport in Lake Nona, Florida (under construction by Lilium). 1c. Archetypes of UAM infrastructure (McKinsey & Company).

5.3. Data and analysis

5.3.1 Study area

The study area is the Greater Los Angeles Area with five counties (Los Angeles County, Orange County, San Bernardino County, Riverside County, and Ventura County). There are several reasons why I choose this area for our study. First, there is an increasing local interest in UAM adoption. In December 2020, Mayor Garcetti announced a public-private partnership between the Los Angeles Department of Transportation and Hyundai Motor Group, this effort aims to introduce UAM to local airspace by 2023 (City of Los Angeles, 2020). One of the early goals of this partnership is to visualize a few vertiports where people can go flying on eVTOL. Second, Southern California has desirable and stable weather for the all-year-round operation of UAM systems as extreme weather conditions and cold temperatures can disturb the daily operation of UAM. Third, this region has seen a significant increase of 'super commuters' whose round trip to work is more than 3 hours. According to the 2018 5-year American Community Survey, there are over 150,000 super commuters, or 1.5% of the total population in Los Angeles County.

5.3.2 Data

The study collected two categories of data for the scenario analyses. On the demand side, the study relied on the U.S. Census Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics that captures home-workplace trips (origin/destination locations) and commuter characteristics at the census block level. The LEHD data provided three categories of sociodemographic characteristics associated with commuting trips, including age groups, income levels, and occupations. The scenario analysis used the LEHD data to estimate the potential travel demand and commuter characteristics under different supply scenarios of vertiports.

On the supply side, the study considered data sources that captured landing site opportunities and spatial constraints. Supply-side opportunities include existing helipads and elevated parking structures collected for the study area. The helipads data was retrieved from the FAA Geohub. The elevated parking structure locations were collected with the google map API. Each elevated parking structure location was manually verified with Google Earth satellite images. Moreover, the supply-side constraints including national airspace zones and local land use constraints (e.g., existing noise levels and schools) were collected for the analysis. The noise data were retrieved from the National Transportation Noise Map which allows the measurement of potential exposure to aviation and highway noise (USDOT, 2022). Then the noise data were recoded into three thresholds, 85dB, 70dB, and 60dB, according to the noise impact classifications provided by the Centers for Disease Control and Prevention (CDC, 2019). Noise at 60dB is the equivalent sound level of normal conversation. People may feel annoyed at 70dB and levels above 85dB are damaging to hearing. No-fly-zone thresholds are defined in accordance with the current UAS airspace regulation (FAA, 2021). Table 5.2 summarized the identified factors and corresponding data sources.

Table 5.2 Factors and data sources

Categories	**Factors**	**Data sources**	**Unit of observation**	**Year of collection**
Demand side	Age groups	Census Origin-Destination Employment Statistics	Census block	2019
	Occupation groups	Census Origin-Destination Employment Statistics	Census block	2019
	Income groups	Census Origin-Destination Employment Statistics	Census block	2019
	Home-workplace trips	Census Origin-Destination Employment Statistics	Census block	2019
	Home-workplace distance	Calculated from the centroids of census blocks	Census block	2019
Supply side	Helipads	The Federal Aviation Administration	Site	2019
	Parking structure	Google earth satellite image/Google map API	Site	2021
	UAS airspace and facility map	The Federal Aviation Administration	Zone	2020
	Schools	The California Department of Education	School	2018
	Noise levels	The United States Department of Transportation	-	2018

5.3.3 Scenario design

The rules for the scenario analysis are presented in Table 5.3, which were divided into five categories. The demand-side rules consider the home-workplace commuters by various population characteristics (e.g., age, income, and occupation) defined by in the LEHD dataset. On the supply-side, the study proposes different sets of airspace and land use constraints. Furthermore, the study defined accessibility rules by walking and driving time from the centroids of workplace/home census blocks. The access time was calculated with the ArcGIS online application by considering the speed limit and average traffic flows on the roads. Demand coverage and block distance rules are introduced to further evaluate the impact of supply-side constraints on commuters' accessibility to vertiports by home-workplace travel distance. As shown in Figure 5.2, five categories of supply-side rules and demand-side rules are mixed to generate the statistics of scenario analyses.

Table 5.3 Summary of scenario analysis rules

Categories	Rules	Description
Demand-side	s000	Total number of home-workplace commuters
	sa01	Home-workplace commuters aged 29 or younger
	sa02	Home-workplace commuters aged 30 to 54
	sa03	Home-workplace commuters aged 55 or older
	se01	Home-workplace commuters with earnings of $1250/month or less
	se02	Home-workplace commuters with earnings of $1251/month to $3333/month
	se03	Home-workplace commuters with earnings greater than $3333/month
	si01	Home-workplace commuters in Goods Producing industry sectors
	si02	Home-workplace commuters in Trade, Transportation, and Utility industry sectors
	si03	Home-workplace commuters in All Other Services industry sectors
Supply-side	A1	<= 200ft pre-approved UAS fly altitude
	A2	<= 300ft pre-approved UAS fly altitude
	A3	<= 400ft pre-approved UAS fly altitude
	S1	>=0.1miles school buffer
	S2	>=0.25miles school buffer
	S3	>=0.5miles school buffer
	N1	>=85dB noise level
	N2	>=70dB noise level
	N3	>=60dB noise level
Accessibility	D1	<= 3min walking by network distance
	D2	<= 5min walking by network distance
	D3	<= 10min walking by network distance
	D4	<= 3min driving by network distance

	D5	<= 5min driving by network distance
	D6	<= 10min driving by network distance
Demand coverage	J1	Home-workplace commuters w/ only home block access
	J2	Home-workplace commuters w/ only workplace block access
	J3	Home-workplace commuters w/ both home and workplace access
Block distance	s000_10	block centroid distance >=10miles
	s000_20	block centroid distance >=20miles
	s000_30	block centroid distance >=30miles

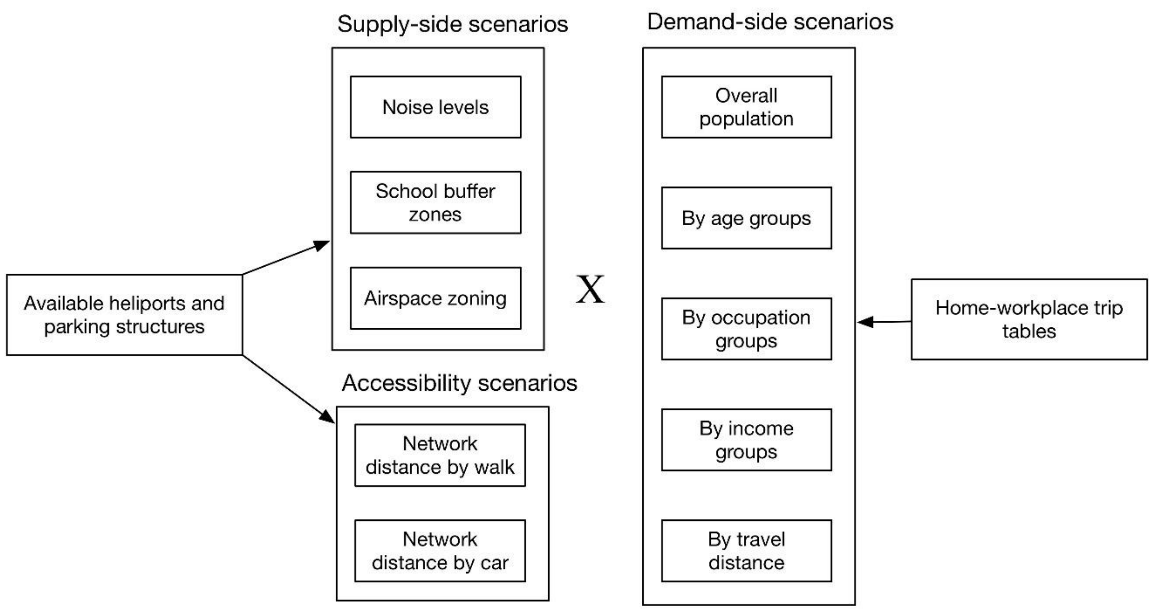

Figure 5.2 Scenario analysis framework

5.4 Results

The impact of spatial constraints on supply-side opportunities is presented in Appendix E. In general, current highway and airport noise have minimal impact on the location choice of vertiports while airspace zoning and school buffer zones can significantly affect the location choice of vertiports. Even under the 200ft flying altitude restriction, there are only 67.2% of available vertiports remain valid choices. If the UAM regulation keeps the current 400ft flying altitude restriction (for small drones) in place, there are only

57.8% of valid sites, less than half of which are parking structures. By mixing the scenarios, the study has been able to generate 27 (3 airspace constraints*3 school buffer constraints*3 noise level constraints) mixed scenarios. The summary statistics of mixed scenarios are presented in Appendix E. The best, the median, and the strictest mixed scenarios are presented in Table 5.4. Under the best-mixed scenario, 61.9% of available sites remain valid, and slightly less than half are parking structures. The percentage of parking structures drops significantly when the constraints become stricter. Under the strictest mixed scenario, about 1/3 of valid sites are parking structures.

Table 5.4 Impact of spatial constraints on supply-side opportunities (single-constraint scenarios and selected mixed-constraint scenarios)

Rules	**Description**	**Helipads**	**Parking Structures**	**Total**	**% Base**
No constraints	All available sites	360	444	804	100.0%
A1	<= 200ft airspace zoning	271	269	540	67.2%
A2	<= 300ft airspace zoning	260	242	502	62.4%
A3	<= 400ft airspace zoning	242	223	465	57.8%
S1	> 0.1mile school buffer	348	402	750	93.3%
S2	> 0.25mile school buffer	294	305	599	74.5%
S3	> 0.5mile school buffer	219	138	357	44.4%
N1	>=85dB noise	360	444	804	100.0%
N2	>=70dB noise	347	441	788	98.0%
N3	>=60dB noise	325	418	743	92.4%
A1*S1*N1	The best mixed scenario	262	236	498	61.9%
A2*S2*N2	The median mixed scenario	217	148	365	45.4%
A3*S3*N3	The strictest mixed scenario	154	56	210	26.1%

Table 5.5 presents the home-workplace commuters that can access the viable vertiports at home and workplace under three different mixed scenarios. A breakdown of commuters with only home access or workplace access to vertiports is presented in

Appendix E. The spatial distribution of valid sites under these mixed scenarios is shown in Figures 5.3a, 5.3b, and 5.3c. These results indicate that most vertiports are not within walkable distance from either the centroids of home census blocks or workplace census blocks in the study area. Under the best scenario, 15.8% of commuters can access the vertiports within 5min driving distance while 70.7% of commuters can access the vertiports with less than 10min of driving. This unique pattern is likely to make parking structures more preferable than helipads when making location decisions of vertiports. Please note that the calculation of driving distance has considered the speed limit of road networks but has not considered the live traffic and traffic light waiting time. Therefore, it is reasonable to believe that the results are optimistic estimates.

Table 5.5 The accessibility of supply-side opportunities for home-workplace commuters (% population with both home and workplace access to vertiports)

Rules	**Description**	**A1*S1*N1 (best)**	**A2*S2*N2 (median)**	**A3*S3*N3 (strictest)**
D1	<= 3min walking distance	0.13%	0.06%	0.00%
D2	<= 5min walking distance	0.37%	0.16%	0.01%
D3	<= 10min walking distance	1.50%	0.63%	0.08%
D4	<= 3min driving distance	4.11%	1.88%	0.36%
D5	<= 5min driving distance	15.80%	8.30%	2.58%
D6	<= 10min driving distance	70.73%	49.48%	27.49%

The horizontal histograms under the maps in Figures 5.3a, 5.3b, and 5.3c present the spatial coverage of different long-distance commuter groups with both home and workplace access to vertiports under three mixed scenarios. Compared to the population average coverage in Table 5.5, the study finds that commuters' accessibility is not very sensitive to travel distance. In other words, long-distance commuters are likely to enjoy equal access to vertiports like average distance commuters. This piece of evidence may support the claim that current infrastructures are spatially ready to accommodate a regional network of urban air mobility. However, extreme-low income and low-income populations have a systematically lower level of accessibility than the population average. Consequently, low-income populations are likely to lag in the adoption of the UAM commute mode. Blue-collar workers and young commuters also have lower-than-average levels of access to vertiports. Such patterns have remained mostly consistent across different accessibility constraints. Appendix E indicates that certain population groups are systematically disadvantaged in terms of their closeness to vertiports regardless of travel distance or accessibility definitions.

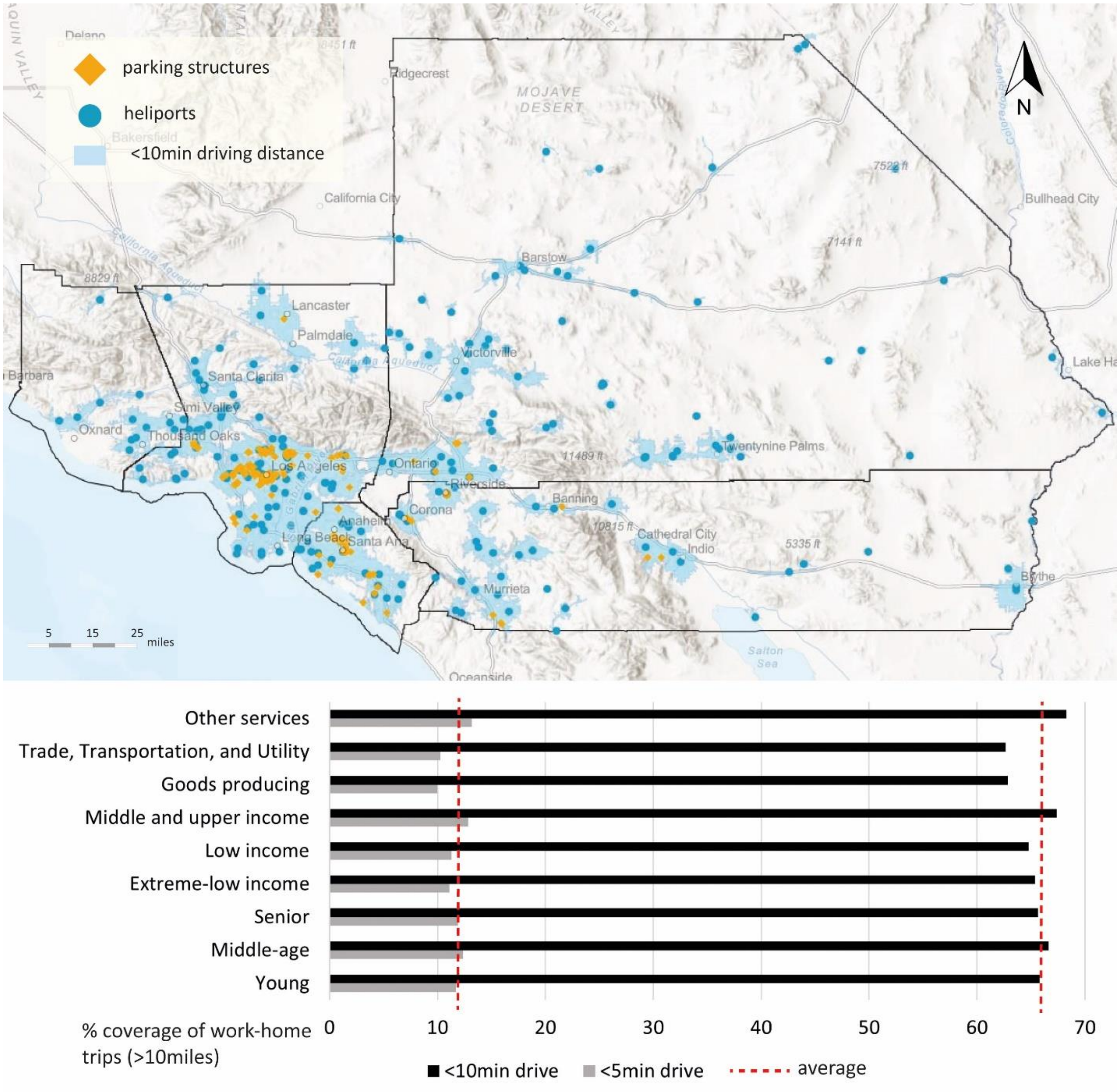

Figure 5.3a Spatial distribution of supply-side opportunities and demand-side coverage by user groups based on the best scenario.

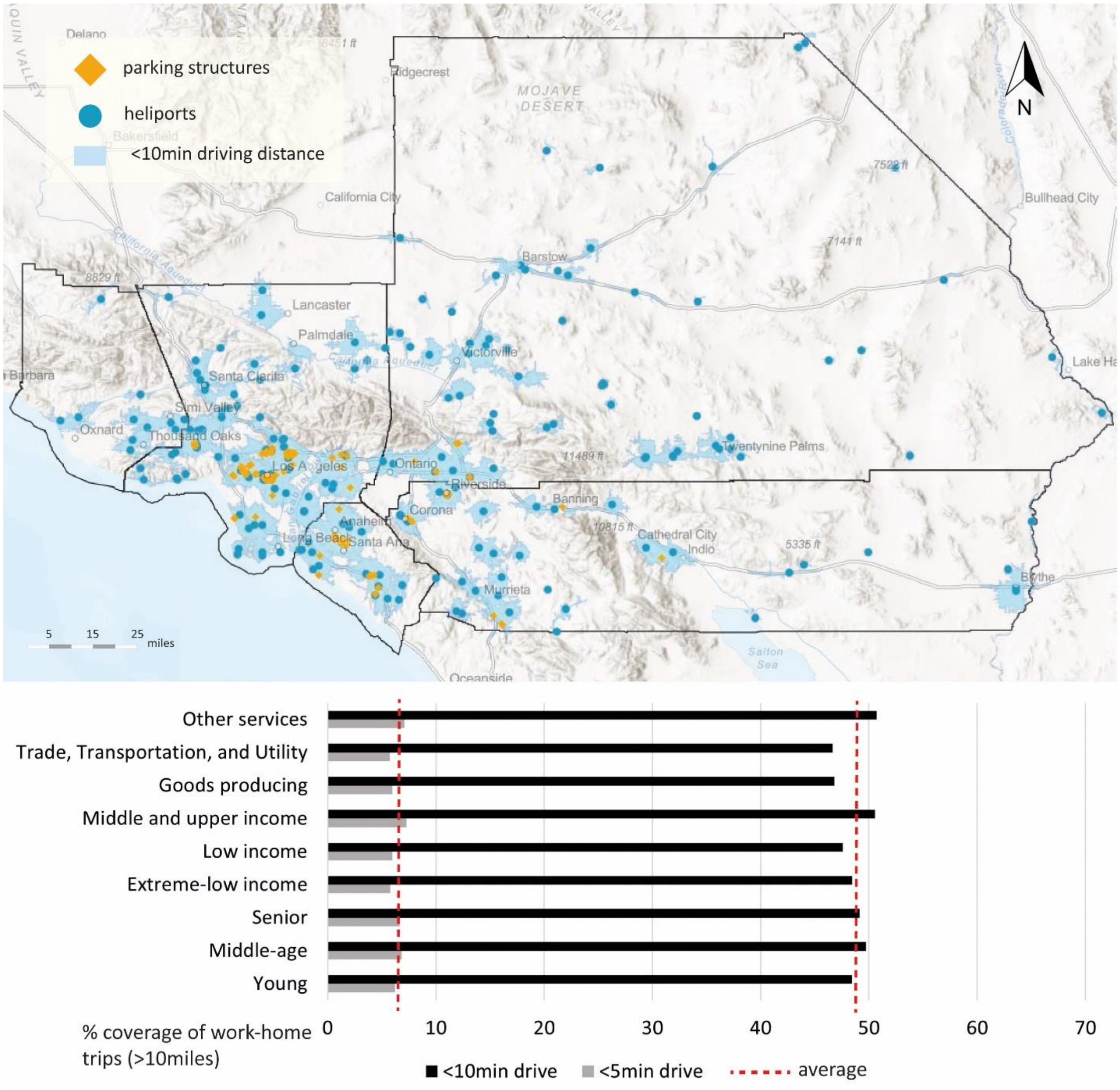

Figure 5.3b Spatial distribution of supply-side opportunities and demand-side coverage by user groups based on the median scenario.

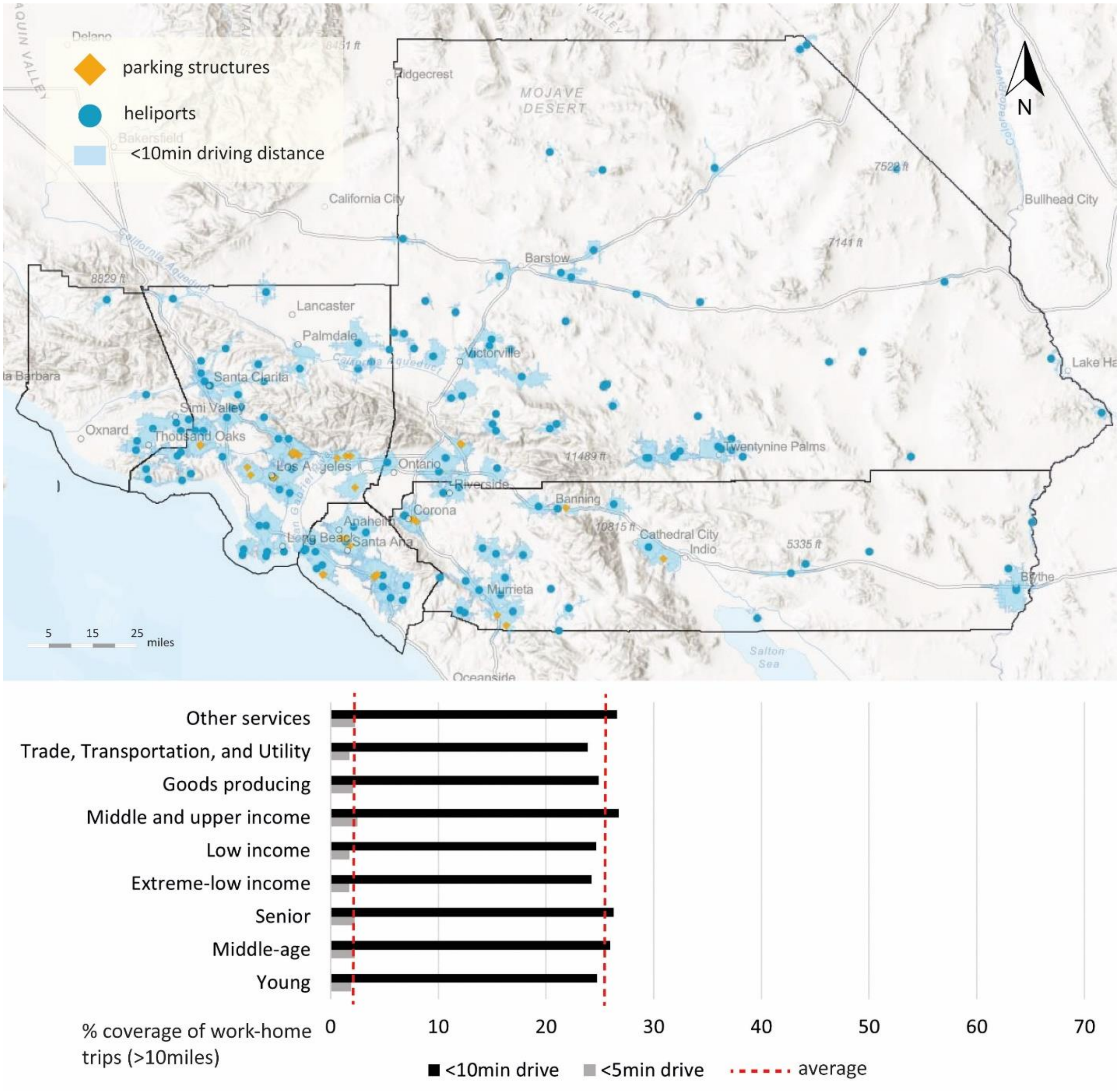

Figure 5.3c Spatial distribution of supply-side opportunities and demand-side coverage by user groups based on the strictest scenario.

Finally, the study has identified the top home-based and workplace-based vertiport candidates based on eligible parking structures for long-distance commuters in the study area from the analysis introduced above (See Figure 5.4). The top home-based vertiports are located in suburban areas while the workplace-based vertiports are located in popular job centers due to the jobs-housing mismatch in Southern California. These potential vertiport candidates represent different strategies that future UAM vertiports might take. For instance, suburban districts can identify many similar locations like Station A, elevated parking structures of a large shopping center, to be adaptively redesigned as vertiports. Station C represents the opportunities to encourage multimodal travel by incorporating UAM into public transport hubs. Station F demonstrates the opportunities of UAM travel mode to serve both regular commuters and be part of the medical emergency services. Moreover, these vertiports may serve as magnets for planners to revitalize urban places by bringing people, activities, and public places together near UAM hubs (e.g., vertiport-oriented communities). Figure 5.5 illustrates an onsite transportation plan to organize UAM traffic and ground traffic for stations B and E.

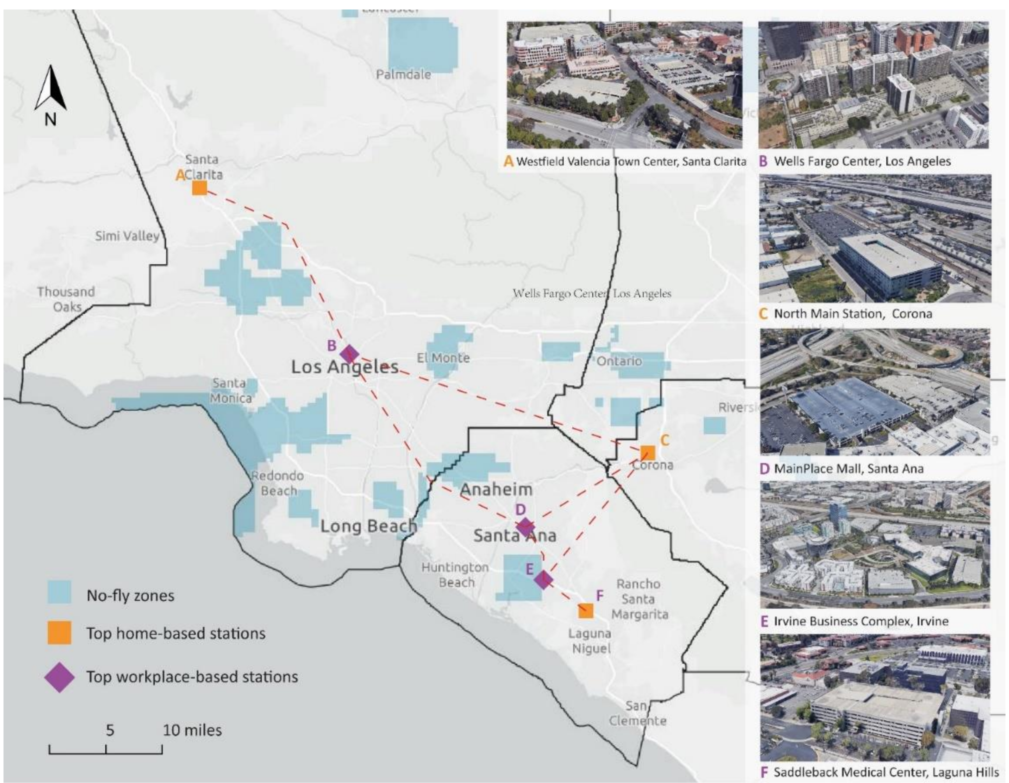

Figure 5.4 A proposed UAM network based on the top home-based and workplace-based stations for residents having commuting trips over 10miles and living within 10min driving distance of vertiports.

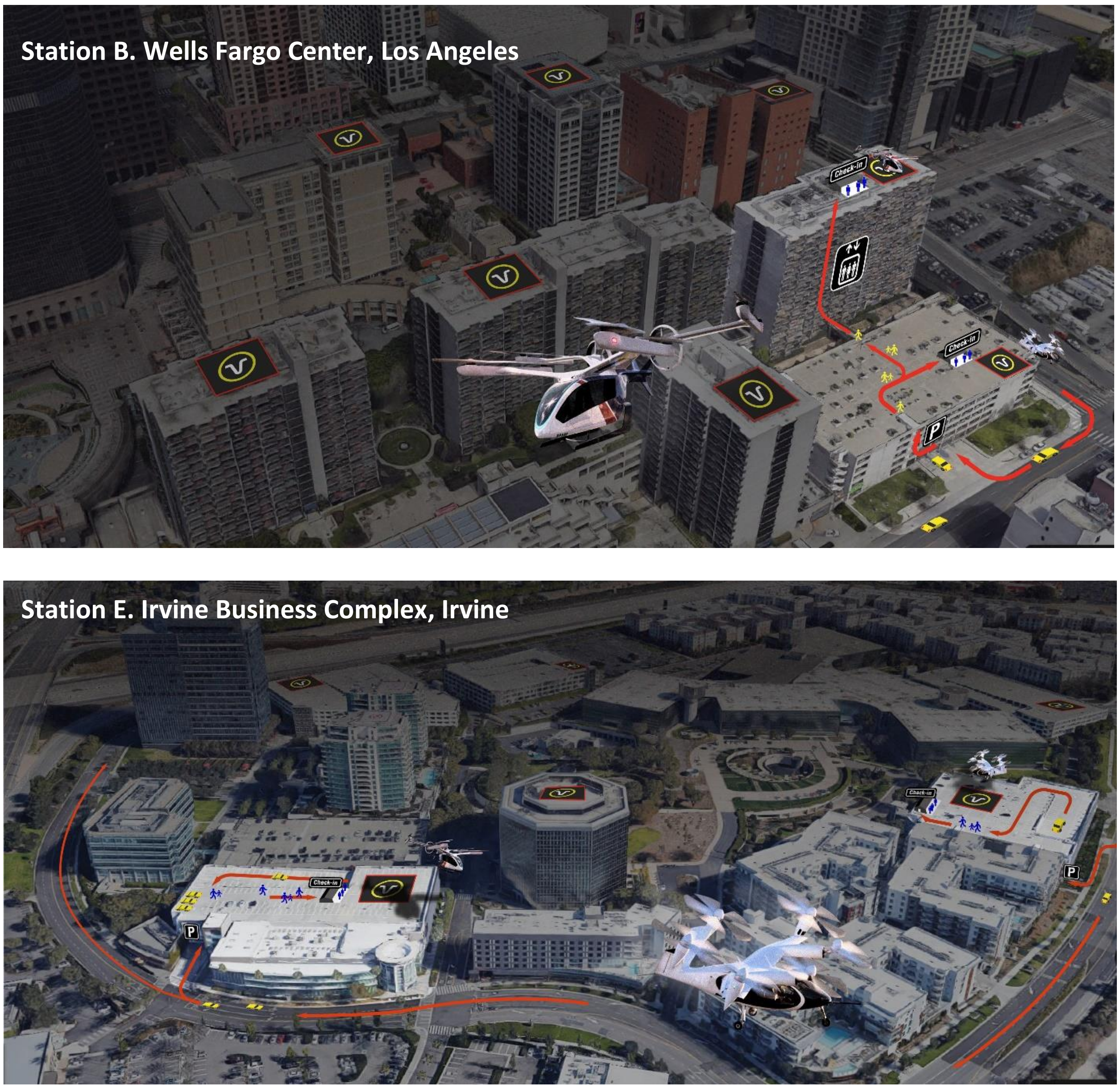

Figure 5.5 A proposed design of UAM vertiport based on existing infrastructure.

5.5 Conclusion and discussion

Urban air mobility holds the promise of becoming a greener, faster, and quieter mode of transportation in the near future (NASA, 2019). While the adoption of UAM is facing many social acceptance barriers (see Al Haddad et al., 2016; Straubinger et al., 2020), identifying feasible landing site locations in built-out metropolitan areas remains a major physical barrier to the mass deployment of UAM. This study provides an initial assessment of potential vertiports locations and associated travel demand in Southern California by employing a systematic scenario analysis. The study suggests that even under the best scenario, most vertiport locations are not within walkable distance for home-workplace commuters. This pattern is rooted in the urban development patterns of the study area but will make park and rides a necessary strategy to access UAM in the future. As a result, parking structures, which are already equipped with parking capacity, become a preferable choice of infrastructure to accommodate the future deployment of UAM service. The study also suggests that extreme low-income populations and blue-collar workers have lower accessibility of vertiports regardless of travel distance. Therefore, future policy interventions might be needed for equitable access to this new mode of transportation. The study also extends the analysis by proposing a network of UAM stations in the study area. The illustration provides possible strategies for planners to identify feasible UAM stations that can facilitate the mass adoption of UAM.

Admittedly, the study has several limitations. For instance, supply-side opportunities are not equal to supply-side capacity. Network design, aircraft specifications, operation costs, routing and scheduling, ingress/egress time, and life cycle cost (LCC) of eVTOL can affect the operation of a UAM system and the feasibility of repurposing the selected landing sites as vertiports. Second, beyond locational constraints, several barriers must be overcome for UAM operations to be integrated safely and efficiently into the urban airspace system. The barriers that are more closely associated with UAM vehicles include ride quality, lifecycle emissions, ease of certification in terms of both time and cost, visual and noise nuisance perceived by the community on the ground, affordability in terms of operating cost, safety in terms of casualties and property damage, and efficiency in terms of energy usage. Furthermore, unlike traditional aviation, which by design typically spends the majority of flight time over sparsely populated areas, UAM operations by definition will generally occur over metropolitan areas that are densely populated in terms of both people and property. As such, a UAM mishap almost certainly would result in substantial damage. Thus, UAM concepts, technologies, and procedures must be designed with safety in mind from the start. As with any new entrant to the airspace, UAM aircraft and operations should be designed in a way to earn acceptance by the public. Concerns about potential privacy violations, auditory and visual disturbances, safety risks, and affordability are some of the significant factors that should be carefully investigated.

Chapter 6. Conclusion

Civilian drones and associated applications, ranging from popular recreational uses and commercial applications to increasingly active roles in planning and governance, have proliferated rapidly in global cities in the past decade. While many regulatory agencies have tried to harness the power of this disruptive technology by encouraging the licensed use of drones in numerous fields, cities are facing challenges to manage drone activities due to the decentralized and highly mobilized characteristics of drones. Despite the proliferation of drones has become a heated topic in practice, academic explorations addressing the fundamental questions pertaining to the diffusion and management of drone technology are neither abundant nor holistic. This dissertation explores the dialectical relationship between disruptive technology and various aspects of cities in the case of civilian drones with the framework of diffusion and management of innovations that have garnered considerable attention since the 1960s. Furthermore, this work provides a first look into a promising evolution of drone technology——UAM by performing a scenarios analysis on the supply-side opportunities and constraints of UAM in built-out metropolitan regions.

Innovation diffusion theory points out that the diffusion and adoption process of innovations share many characteristics across time and space (Rogers, 2003). However, early adopters' demographic profiles can be different given the target user groups and the context of the diffusion process. Chapters 2 and 3 investigate the diffusion dynamics of civilian drones at different geographical scales. The results of both studies indicate that areas with higher early drone adoption are on average younger, whiter, and more affluent and digitally connected even when spatial-dependence effects are taken into consideration. Therefore, this work sheds light on the broad policy interventions to reduce the information inequality in the adoption of innovations. As suggested by the grand tech-society theories reviewed in Chapter 1, social constructs are not only reacting but shaping and iteratively reshaping the power of disruptive technology. To explore the social construct that is shaping drone technology, Chapter 4 examines the dynamics of local drone policy adoption, focusing on California, which has the largest population of drones currently registered in the United States. The results indicate that policy adoption at the local level is shaped by both municipal capacity and motivation factors, including the actions of neighboring cities. Like the results from Chapters 2 and 3, Chapter 4 provides evidence of disparities associated with socio-demographics in local drone policy adoption, calling for more attention to support disadvantaged local agencies in addressing the challenges of disruptive technologies. However, this study does necessarily suggest that drone is either a necessity or a good choice for all communities. The broad implication from this consistent finding is unfolded in two ways: 1) how could technology improve the life opportunities of disadvantaged groups? And 2) how could planners/planning policies help mitigate the negative impact of technology in disadvantaged communities? In terms of drone technology, disadvantaged groups can benefit from the technology by registering as commercial drone pilots that offer flexible employment opportunities in various fields. For planners and policy makers, the study calls for regional coordination among localities in response to the emerging challenges of disruptive technology. Moreover, the evolving nature of technology indicates that drone technology is likely to evolve into other promising forms. This work takes a first look into a promising future of drone——UAM by assessing the supply-side opportunities of UAM in a built-out metropolitan area (Southern California) with a systematic scenario analysis. Although supply-side opportunities like helipads and elevated parking structures are widely available in the study area, spatial constraints like noise levels, school zones, and no-fly-zones are going to significantly reduce the location choices of vertiports, and certain population groups are likely to be placed in a disadvantaged position to access the UAM commute mode if no new vertiports are considered.

I acknowledge that this work has several shortcomings. The first constraint is the lack of causal conclusions between regulations and drone proliferation. Additional quasi-experimental approaches, like difference-in-differences and propensity score matching, are needed to make causal inferences about the factors that prompt policy adoption. The second limitation of the study is that, despite many identified key factors associated with the adoption of local drone policy, I did not ground truth the policy adoption mechanisms with the necessary groundwork. Due to the pluralistic nature of the policy adoption process drone policy adoption might be translated in various ways by diverse stakeholders. The third limitation is a simplified approach through which I estimate travel demand associated with different UAM supply-side scenarios, given that numerous factors like pricing, route configurations, and scheduling can affect the UAM demand in complex ways.

As a result, I propose future studies include a broader data collection of the policy adoption process, ground-truthing the policy dynamics from the perspective of diverse stakeholders, and travel demand modeling to examine more diverse and detailed aspects of drone technology and shed light on the urban management of other disruptive technologies. Moreover, emerging evidence suggests the existence of a dynamic relationship between drone technology and social constructs over time. In the early phases of adoption, the growth rate of drones accelerated year-over-year when regulations were scarce at all levels of government. The growth curve of drone registrations went through the inflection point when major regulatory interventions were introduced around 2016. Although this growth pattern can be explained by the innovation diffusion theory (Rogers, 2003) in which the adoption of many innovations follows a similar S-shaped growth curve as the majority of population are not pioneering innovation adopters (or risk-takers), the potential bidirectional causal relationship between innovation adoption and innovation regulation deserves more scholarly attention in the future. There was also evidence that the changing behaviours of the supply-side of the drone industry might affect the patterns of drone adoption pattern and the drone registration data. In recent year, many popular drone makers have shifted to produce light-weight drones below 250 grams without compromising drones' technical capacities while the FAA only mandated the registration of drones above 250 grams. This supply-side change was in part induced by the regulations and to meet the market demand for smaller and more portable drones.

Despite the limitations, this dissertation is one of the pioneering works that systematically examines the diffusion and regulation patterns of civilian drones in the United States, using innovative sources of data and spatial-temporal analysis. Moreover, this work provides a supply-side scenario analysis of UAM by assuming existing urban infrastructure can facilitate the mass deployment of UAM services in built-out metropolitan areas. The non-deterministic analytical framework of this work can be applied to the exploration of dynamic relationships between other disruptive technologies and cities.

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Appendix A. Optimized Hotspot Change Analysis

The study proposes the use of optimized Getis–Ord G* spatial statistics in ArcGIS to identify hot/cold spots of drone adoption across times to help the researcher to explore the general spatial distribution pattern of the dependent variable. The application of the method has been demonstrated in crime analysis, epidemiology, voting pattern analysis, economic geography, retail analysis, traffic incident analysis, and demographics. Calculation of the Getis–Ord local statistic can be performed in ArcGIS Desktop. The function is given as:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{n\sum_{j=1}^{n} w_{i,j}^2 - (\sum_{j=1}^{n} w_{i,j})^2}{n-1}}} \qquad (1)$$

where x_j is the attribute value for feature j, $w_{i,j}$ is the spatial weight between feature i and j, n is the total number of features and:

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n} \qquad (2)$$

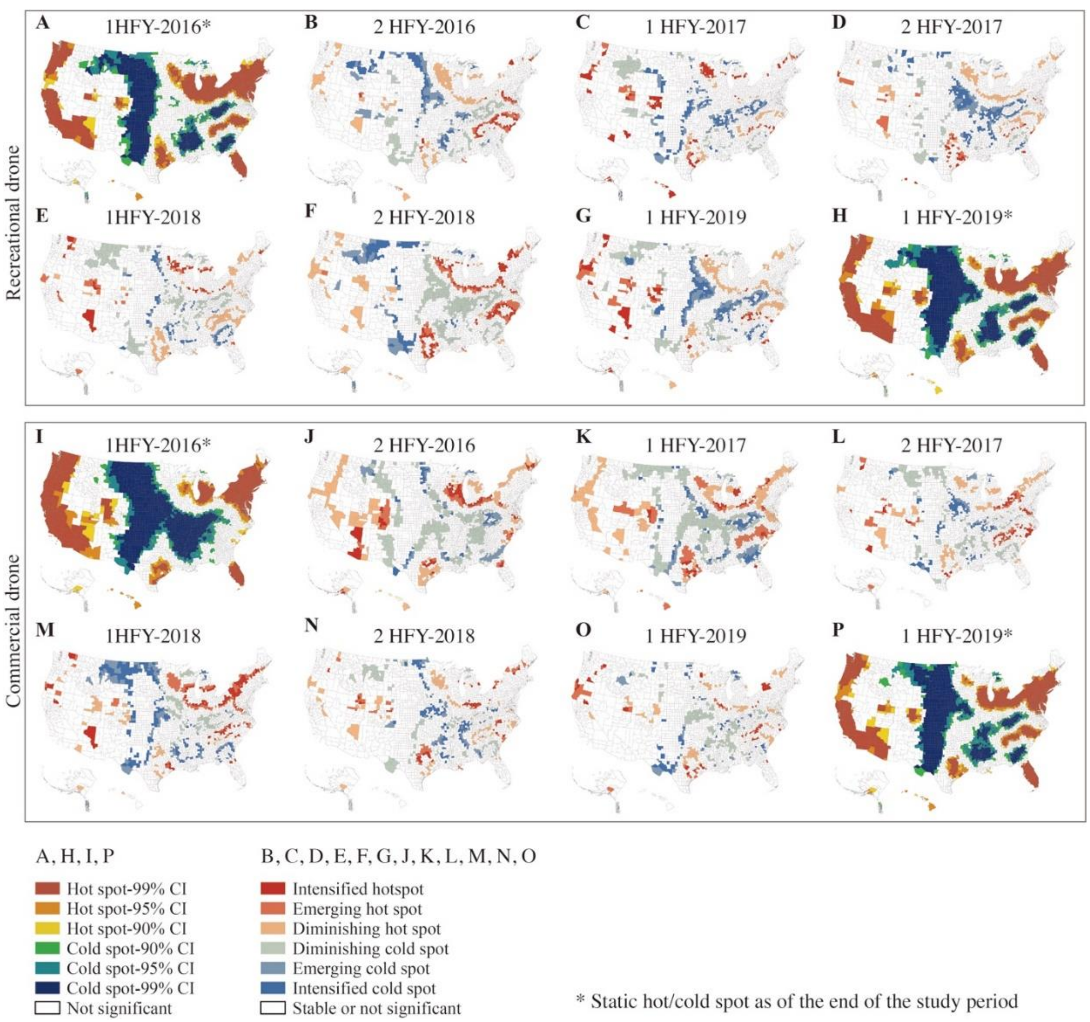
$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \bar{X}^2} \qquad (3)$$

The Gi* statistic returned for each feature in the dataset is a Z score. For statistically significant positive Z scores, the larger the Z score is, the more intense the clustering of high values (hot spot). For statistically significant negative Z scores, the smaller the Z score is, the more intense the clustering of low values (cold spot). The Optimized Hot Spots Analysis tool in ArcGIS can automatically aggregates point data, identify an appropriate scale of analysis, and correct for both multiple testing and spatial dependence. Apart from the static hotspot identification in the starting and ending periods, the study also pays attention to the spatial-temporal change of hot/cold spots (e.g., emerging hotspots, intensified hotspots, etc.). Table 2.3 presents a classification matrix for various hotspot changes between two consecutive periods of study.

Table 2.3 Types of hot spot change

		T						
		Cold 99%	Cold 95%	Cold 90%	Insignificant	Hot 90%	Hot 95%	Hot 99%
T+Δt	Cold 99%	S	IC	IC	EC	EC	EC	EC
	Cold 95%	DC	S	IC	EC	EC	EC	EC
	Cold 90%	DC	DC	S	EC	EC	EC	EC
	Insignificant	DC	DC	DC	S	DH	DH	DH
	Hot 90%	EH	EH	EH	EH	S	DH	DH
	Hot 95%	EH	EH	EH	EH	IH	S	DH
	Hot 99%	EH	EH	EH	EH	IH	IH	S

Notes: S-Stable or Insignificant; DC-Diminishing cold spot; EC-Emerging cold spot; IC-Intensified cold spot; DH-Diminishing hot spot; EH-Emerging hotspot; IH-Intensified hotspot.



Hot spot and cold spot change over time

Appendix B. Supplementary Analyses of Drone Adoption Pattens at Zip Code Level

OLS models of drone adoption: Comparison among different racial/ethnic groups

Variable (N=572)	OLS/Asian.PI		OLS/Black		OLS/Hispanic	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Hobby drone adoption rate (DV)						
Age	1.935 ***	0.278	2.098 ***	0.277	2.519 ***	0.294
Age.Sq	-0.019 ***	0.004	-0.022 ***	0.004	-0.030 ***	0.005
Log.Income	21.141 ***	2.253	20.001 ***	2.122	16.94 ***	2.210
Pct.HighSpeedBroadband	10.415 *	4.605	10.919 *	4.575	11.213 *	4.581
Pct.TechWorkers	129.237 ***	24.242	120.239 ***	22.530	67.51 **	24.825
Pct.ArtsWorkers	119.321 ***	20.934	124.401 ***	20.592	83.767 ***	21.645
Housing.Density	-0.242	0.345	-0.195	0.322	-0.176	0.316
Pct.Residential	-14.11 ***	3.406	-15.443 ***	3.391	-11.876 ***	3.361
Pct.Openspace&Recreation	-14.447	10.363	-18.791	10.356	-16.769	10.126
Pct.Office&Commercial	2.762	8.598	-0.023	8.562	2.012	8.414
Coast	15.298 ***	2.726	15.251 ***	2.669	14.863 ***	2.637
Pct.Asian.PI	-0.004	0.002				
Pct.Black			-0.014 ***	0.004		
Pct.Hispanic					-0.034 ***	0.007
Intercept	-246.854 ***	24.609	-232.246 ***	23.181	-194.109 ***	24.567
R-squared	0.530		0.538		0.550	
AIC	4743.085		4733.189		4718.446	

Note: * significance level of 0.05, ** significance level of 0.01, *** significance level of 0.001

SLM models of drone adoption: Comparison among different racial/ethnic groups

Variable (N=572)	SLM/Asian.PI		SLM/Black		SLM/Hispanic	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Hobby drone adoption rate (DV)						
Age	1.970 ***	0.268	2.061 ***	0.268	2.574 ***	0.282
Age.Sq	-0.019 ***	0.004	-0.021 ***	0.004	-0.031 ***	0.004
Log.Income	18.155 ***	2.234	17.201 ***	2.136	13.357 ***	2.195
Pct.HighSpeedBroadband	8.344 *	4.374	8.931 *	4.339	8.187 *	4.240
Pct.TechWorkers	120.314 ***	23.431	110.245 ***	21.940	51.994 *	23.971
Pct.ArtsWorkers	112.500 ***	20.224	118.204 ***	20.005	75.324 ***	20.836
Housing.Density	-0.378	0.334	-0.393	0.315	-0.351	0.305
Pct.Residential	-13.868 ***	3.285	-14.979 ***	3.289	-11.548 ***	3.230
Pct.Openspace&Recreation	0.221	10.313	-3.844	10.501	-1.353	10.019
Pct.Office&Commercial	6.206	8.314	3.743	8.337	5.503	8.101
Coast	13.061 ***	2.658	13.428 ***	2.615	12.632 ***	2.557
Pct.Asian.PI	-0.006	0.005				
Pct.Black			-0.010 *	0.004		
Pct.Hispanic					-0.036 ***	0.007
Intercept	-237.814 ***	23.785	-223.735 ***	22.543	-179.113 ***	23.716
Rho	0.751 ***	0.130	0.688 ***	0.142	0.784 ***	0.122
R-squared	0.553		0.556		0.575	
LM	28.392		20.882		35.984	
AIC	4723.021		4718.303		4694.467	

Note: * significance level of 0.05, ** significance level of 0.01, *** significance level of 0.001

SEM models of drone adoption: Comparison among different racial/ethnic groups

Variable (N=572)	SEM/Asian.PI		SEM/Black		SEM/Hispanic	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Hobby drone adoption rate (DV)						
Age	1.864 ***	0.271	1.997 ***	0.270	2.552 ***	0.286
Age.Sq	-0.019 ***	0.004	-0.021 ***	0.004	-0.031 ***	0.004
Log.Income	20.612 ***	2.287	19.873 ***	2.193	15.317 ***	2.325
Pct.HighSpeedBroadband	9.553 *	4.587	8.987 *	4.582	8.708 *	4.402
Pct.TechWorkers	126.693 ***	24.412	119.830 ***	22.822	56.496 *	25.162
Pct.ArtsWorkers	139.136 ***	22.664	142.586 ***	22.489	97.479 ***	23.192
Housing.Density	-0.061	0.361	-0.022	0.347	-0.020	0.338
Pct.Residential	-13.445 ***	3.439	-14.534 ***	3.446	-11.599 ***	3.360
Pct.Openspace&Recreation	-13.082	12.250	-16.742	12.178	-12.145	11.990
Pct.Office&Commercial	2.401	8.401	-0.127	8.410	1.731	8.170
Coast	12.305 ***	2.827	12.359 ***	2.803	11.328 ***	2.722
Pct.Asian.PI	-0.003	0.005				
Pct.Black			-0.011 **	0.004		
Pct.Hispanic					-0.040 ***	0.007
Intercept	-233.028 ***	25.735	-224.429 ***	24.352	-166.65 ***	26.902
Lambda	0.830 ***	0.134	0.787 ***	0.160	0.868 ***	0.108
R-squared	0.523		0.532		0.542	
LM	12.31		7.513		21.452	
AIC	4733.444		4727.261		4702.797	

Note: * significance level of 0.05, ** significance level of 0.01, *** significance level of 0.001

OLS models of different categories of variables

Variable (N=572)	OLS: M1		OLS: M2		OLS: M3		OLS: M4	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Hobby drone adoption rate (DV)								
Socioeconomics								
Age	1.601 ***	0.388					2.973 ***	0.526
Age.Sq	-0.011 *	0.006					-0.033 ***	0.008
Log.Income	26.070 ***	3.293					23.829 ***	3.998
Pct.TechWorkers	200.798 ***	39.429					202.686 ***	44.875
Pct.ArtsWorkers	237.959 ***	30.962					206.476 ***	37.557
Land use and broadband								
Pct.HighSpeedBroadband			32.444 ***	9.333			21.901 **	7.583
Housing.Density			0.183	0.601			-0.099	0.588
Pct.Residential			5.296	6.467			-20.331 ***	5.820
Pct.Openspace&Recreation			13.038	21.686			-17.412	17.643
Pct.Office&Commercial			18.039	17.911			15.528	14.526
Coast			36.923 ***	5.514			15.130 ***	4.596
Race and ethnicity								
Pct.Asian.PI					0.032 ***	0.008	-0.012	0.009
Pct.Black					-0.009	0.008	-0.015 *	0.007
Pct.Hispanic					-0.083 ***	0.008	-0.018	0.012
Intercept	-304.415 ***	36.114	21.305 **	6.745	64.617 ***	3.605	-284.305 ***	44.535
R-squared	0.406		0.114		0.215		0.560	
AIC	5375.494		5606.001		5530.740		5239.455	

Note: * significance level of 0.05, ** significance level of 0.01, *** significance level of 0.001

Appendix C. Examples of Drone Policies

1. City of Laguna Niguel (adopted in 12/2002)

Sec. 13-1-81. PROHIBITION OF POWERED AIRPLANES.

The flying of electric or gasoline-powered model airplanes or aircraft at the park is prohibited.

(Ord. No. 2002-123, § 2, 12-17-02)

Source: https://www.cityoflagunaniguel.org/66/Municipal-Code

2. City of Porterville (adopted in 06/2009)

Sec. 4-11.35: MODEL AND RADIO CONTROLLED AIRCRAFT:

No model or radio controlled aircraft will be allowed on or above Porterville municipal airport property or on any city property adjacent to the Porterville municipal airport or any property within the city of Porterville that is under or near the pattern for aircraft or air vehicles at the Porterville municipal airport. (Ord. 1755, 6-2-2009)

Source: https://codelibrary.amlegal.com/codes/portervilleca/latest/porterville_ca/0-0-0-1

3. City of Los Angeles (adopted in 12/2015)

Sec. 56.31. UNMANNED AIRCRAFT SYSTEMS.

(a) For purposes of this section:

1. "Unmanned Aircraft" shall mean an aircraft, including, but not limited to, an aircraft commonly known as a drone, that is operated without the possibility of direct human intervention from within or on the aircraft.

2. "Unmanned Aircraft System" shall mean an Unmanned Aircraft and associated elements, including, but not limited to, any communication links and components that control the Unmanned Aircraft.

3. “Person” shall have the same meaning as set forth in Subsection (a) of Section 11.01 of this Code.

4. “Model Aircraft” shall mean an Unmanned Aircraft or Unmanned Aircraft System operated by any Person strictly for hobby or recreational purposes.

5. “Civil UAS” shall mean an Unmanned Aircraft or Unmanned Aircraft System operated by any Person for any purposes other than strictly hobby or recreational purposes, including, but not limited to, commercial purposes or in furtherance of, or incidental to, any business or media service or agency.

6. “Public UAS” shall mean an Unmanned Aircraft or Unmanned Aircraft System operated by any public agency for government-related purposes.

(b) The following shall apply to the operation of any Model Aircraft within the City of Los Angeles:

1. No Person shall operate any Model Aircraft within the City of Los Angeles and within 5 miles of an airport without the prior express authorization of the airport air traffic control tower.

2. No Person shall operate any Model Aircraft within the City of Los Angeles in a manner that interferes with manned aircraft and shall always give way to any manned aircraft.

3. No Person shall operate any Model Aircraft within the City of Los Angeles beyond the visual line of sight of the person operating the Model Aircraft. The operator must use his or her own natural vision (which includes vision corrected by standard eyeglasses or contact lenses) to observe the Model Aircraft. People other than the operator may not be used in lieu of the operator for maintaining visual line of sight. Visual line of sight means that the operator has an unobstructed view of the Model Aircraft. The use of vision-enhancing devices, such as binoculars, night vision goggles, powered vision magnifying devices, and goggles or other devices designed to provide a “first-person view” from the model, do not constitute the visual line of sight of the person operating the Model Aircraft.

4. No Person shall operate any Model Aircraft within the City of Los Angeles other than during daylight hours defined as between official sunrise and official sunset for local time.

5. No Person shall operate any Model Aircraft within the City of Los Angeles more than 400 feet above the earth's surface.

6. Excluding takeoff and landing, no Person shall operate any Model Aircraft within the City of Los Angeles closer than 25 feet to any individual, except the operator or the operator's helper(s).

(c) The following shall apply to the operation of any Model Aircraft or Civil UAS within the City of Los Angeles:

1. No Person shall operate any Model Aircraft or Civil UAS within the City of Los Angeles in a manner that is prohibited by any federal statute or regulation governing aeronautics.

2. No Person shall operate any Model Aircraft or Civil UAS within the City of Los Angeles in violation of any temporary flight restriction (TFR) or notice to airmen (NOTAM) issued by the Federal Aviation Administration.

3. No Person shall operate any Model Aircraft or Civil UAS within the City of Los Angeles in a careless or reckless manner so as to endanger the life or property of another. The standard for what constitutes careless and reckless operation under this section shall be the same as the standard set forth in any federal statutes or regulations governing aeronautics including, but not limited to, Federal Aviation Rule 91.13.

(d) It shall be unlawful for any Person to violate or fail to comply with this section. Any Person violating the provisions of this section shall be guilty of a misdemeanor and subject to the provisions of Subsection (m) of Section 11.00 of this Code.

(e) This section shall not apply to any Public UAS operated pursuant to, and in compliance with, the terms and conditions of any current and enforceable authorization granted by the Federal Aviation Administration.

Source: https://codelibrary.amlegal.com/codes/los_angeles/latest/lamc/0-0-0-107363

Appendix D. Supplementary Analyses of the Adoption Patterns of Drone Policies

	Long-term (N = 474)	Short-term (N = 465)	
		Basic model	Full model
Log.Population	0.547 ***	0.516 **	0.430 **
	(0.159)	(0.170)	(0.137)
Pop.Density	0.156 ***	0.167 ***	0.144 **
	(0.042)	(0.044)	(0.044)
Coastal.Cities	0.560 *	0.478	-0.057
	(0.279)	(0.355)	(0.390)
Airports	0.025	0.030	0.033
	(0.072)	(0.071)	(0.072)
Fiscal.Capacities	0.160	0.084	-0.237
	(0.134)	(0.274)	(0.305)
Law.Enforcement	-4.118	-2.180	-0.892
	(9.867)	(9.030)	(7.092)
City.Governance	-0.114	-0.483	-0.684
	(0.312)	(0.369)	(0.381)
Percent.High.Edu	1.972 *	2.404 *	1.342
	(0.985)	(1.135)	(1.278)
Percent.Non.White	-2.481 *	-1.940 *	-2.110 *
	(1.096)	(0.978)	(1.070)
Percent.Hispanic	-0.168	-0.694	-0.365
	(1.059)	(1.040)	(1.146)
Nearby.DronePolicy			0.328 *
			(0.135)
PBOC.Access			2.613 ***
			(0.747)
Log.Comm.Drones			0.019
			(0.038)
Log.Rec.Drones			0.238
			(0. 243)

Log.Incidents			0.052 *
			(0.023)
Constant	-8.661 ***	-8.398 **	-3.306
	(1.999)	(2.744)	(3.600)
Log likelihood	-193.725	-173.758	-161.255
Pseudo R^2	0.284	0.287	0.341

Notes: Standard errors are in parentheses.

* Significance level of 0.05, ** Significance level of 0.01, *** Significance level of 0.001.

Appendix E Summary Statistics of UAM Scenario Analysis

Imapct of spatial constraints on supply-side opportunities (mixed-constraint scenarios)

ID	Scenarios (3*3*3=27)	Helipads	Parking Structures	Total	% base
1	A1*S1*N1*(the best)*	262	236	498	61.9%
2	A1*S1*N2	261	234	495	61.6%
3	A1*S1*N3	250	227	477	59.3%
4	A1*S2*N1	222	163	385	47.9%
5	A1*S2*N2	221	162	383	47.6%
6	A1*S2*N3	214	159	373	46.4%
7	A1*S3*N1	170	66	236	29.4%
8	A1*S3*N2	169	66	235	29.2%
9	A1*S3*N3	167	65	232	28.9%
10	A2*S1*N1	251	210	461	57.3%
11	A2*S1*N2	250	208	458	57.0%
12	A2*S1*N3	243	202	445	55.3%
13	A2*S2*N1	218	149	367	45.6%
14	A2*S2*N2*(the median)*	217	148	365	45.4%
15	A2*S2*N3	210	145	355	44.2%
16	A2*S3*N1	169	60	229	28.5%
17	A2*S3*N2	168	60	228	28.4%
18	A2*S3*N3	154	56	210	26.1%
19	A3*S1*N1	233	192	425	52.9%
20	A3*S1*N2	232	190	422	52.5%
21	A3*S1*N3	227	184	411	51.1%
22	A3*S2*N1	201	135	336	41.8%
23	A3*S2*N2	200	134	334	41.5%
24	A3*S2*N3	195	131	326	40.5%
25	A3*S3*N1	157	57	214	26.6%
26	A3*S3*N2	156	57	213	26.5%
27	A3*S3*N3 *(the strictest)*	154	56	210	26.1%

Accessibility of supply-side opportunities for long-distance (>=10miles) commuters

*Supply-A1*S1*N1 (best)*	Home access only	Workplace access only	Both home and workplace access	Home access/workplace access ratio
<= 3min walking distance	0.48%	8.35%	0.03%	5.72%
<= 5min walking distance	1.00%	11.66%	0.11%	8.58%
<= 10min walking distance	2.81%	17.43%	0.57%	16.14%
<= 3min driving distance	6.57%	23.09%	2.24%	28.45%
<= 5min driving distance	15.10%	30.69%	11.68%	49.20%
<= 10min driving distance	10.93%	18.34%	64.02%	59.59%
*Supply-A2*S2*N2 (median)*	Home access only	Workplace access only	Both home and workplace access	Home access/workplace access ratio
<= 3min walking distance	0.30%	6.47%	0.01%	4.70%
<= 5min walking distance	0.64%	8.99%	0.05%	7.12%
<= 10min walking distance	1.79%	13.12%	0.23%	13.64%
<= 3min driving distance	4.70%	18.02%	1.03%	26.05%
<= 5min driving distance	12.57%	27.16%	6.41%	46.27%
<= 10min driving distance	16.57%	24.38%	47.61%	67.94%
*Supply-A3*S3*N3 (strictest)*	Home access only	Workplace access only	Both home and workplace access	Home access/workplace access ratio
<= 3min walking distance	0.09%	1.64%	0.00%	5.26%
<= 5min walking distance	0.22%	2.73%	0.01%	7.92%
<= 10min walking distance	0.66%	6.04%	0.04%	10.90%
<= 3min driving distance	2.17%	9.85%	0.23%	22.01%
<= 5min driving distance	7.86%	18.74%	2.07%	41.94%
<= 10min driving distance	22.12%	27.39%	24.87%	80.76%

Accessibility of supply-side opportunities for long-distance (>=20miles) commuters

*Supply-A1*S1*N1 (best)*	Home access only	Workplace access only	Both home and workplace access	Home access/workplace access ratio
<= 3min walking distance	0.40%	7.85%	0.02%	5.05%
<= 5min walking distance	0.84%	10.92%	0.08%	7.71%
<= 10min walking distance	2.43%	16.64%	0.42%	14.61%
<= 3min driving distance	6.00%	22.36%	1.92%	26.85%
<= 5min driving distance	14.45%	30.88%	10.65%	46.79%
<= 10min driving distance	11.85%	21.42%	60.93%	55.31%
*Supply-A2*S2*N2 (median)*	Home access only	Workplace access only	Both home and workplace access	Home access/workplace access ratio
<= 3min walking distance	0.26%	6.17%	0.01%	4.13%
<= 5min walking distance	0.54%	8.52%	0.04%	6.39%
<= 10min walking distance	1.54%	12.57%	0.21%	12.28%
<= 3min driving distance	4.24%	17.44%	1.02%	24.33%
<= 5min driving distance	11.85%	26.78%	6.28%	44.26%
<= 10min driving distance	16.48%	25.71%	46.34%	64.10%
*Supply-A3*S3*N3 (strictest)*	Home access only	Workplace access only	Both home and workplace access	Home access/workplace access ratio
<= 3min walking distance	0.09%	1.67%	0.00%	5.26%
<= 5min walking distance	0.21%	2.77%	0.01%	7.65%
<= 10min walking distance	0.62%	6.06%	0.04%	10.22%
<= 3min driving distance	2.12%	9.88%	0.26%	21.47%
<= 5min driving distance	7.92%	18.67%	2.19%	42.43%
<= 10min driving distance	21.68%	27.21%	25.72%	79.68%

Accessibility of supply-side opportunities for long-distance (>=30miles) commuters

*Supply-A1*S1*N1 (best)*	Home access only	Workplace access only	Both home and workplace access	Home access/workplace access ratio
<= 3min walking distance	0.37%	7.29%	0.02%	5.08%
<= 5min walking distance	0.81%	10.10%	0.06%	8.00%
<= 10min walking distance	2.38%	15.54%	0.33%	15.33%
<= 3min driving distance	6.02%	21.37%	1.59%	28.16%
<= 5min driving distance	14.80%	30.50%	9.55%	48.52%
<= 10min driving distance	12.66%	23.28%	58.29%	54.39%
*Supply-A2*S2*N2 (median)*	Home access only	Workplace access only	Both home and workplace access	Home access/workplace access ratio
<= 3min walking distance	0.24%	5.78%	0.01%	4.11%
<= 5min walking distance	0.52%	7.91%	0.03%	6.62%
<= 10min walking distance	1.50%	11.75%	0.15%	12.78%
<= 3min driving distance	4.21%	16.69%	0.80%	25.24%
<= 5min driving distance	12.03%	26.37%	5.37%	45.64%
<= 10min driving distance	17.32%	27.35%	43.49%	63.33%
*Supply-A3*S3*N3 (strictest)*	Home access only	Workplace access only	Both home and workplace access	Home access/workplace access ratio
<= 3min walking distance	0.09%	1.59%	0.00%	5.38%
<= 5min walking distance	0.21%	2.60%	0.00%	8.12%
<= 10min walking distance	0.59%	5.68%	0.03%	10.39%
<= 3min driving distance	2.04%	9.41%	0.21%	21.66%
<= 5min driving distance	7.85%	18.04%	1.92%	43.54%
<= 10min driving distance	22.10%	27.91%	23.75%	79.18%