RESEARCH REPORT

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Benchmarking Smart City Technology Adoption in California: An Innovative Web Platform for Exploring New Data and Tracking Adoption

November 2021

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16. Abstract

In recent years, "smart city" technologies have emerged that allow cities, counties, and other agencies to manage their infrastructure assets more effectively, make their services more accessible to the public, and allow citizens to interface with new web-and mobile-based alternative service providers. This project developed an innovative user-friendly web interface for local and state policymakers that tracks and displays information on the adoption of such technologies in California across the policing, transportation, and water and wastewater sectors for a comprehensive set of local service providers: connectedgov.berkeley.edu. Contrary to conventional smart city indices, our platform allows users to view rates of adoption in maps that attribute adoption to the local public agencies or service providers actually procuring or regulating the technologies in question. Users can construct indices or view technologies one by one. Users can also explore the relationship between technology adoption and local service area conditions and demographics, or download the raw data and scripts used to collect it. This report illustrates the utility of the data we have collected, and the analytics one can perform using our web interface through an analysis of the rollout of three technologies in the transportation sector: electric vehicle (EV) chargers, transportation network company (TNC) service areas, and micro-mobility services across California.

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Benchmarking Smart City Technology Adoption in California: An Innovative Web Platform for Exploring New Data and Tracking Adoption

November 2021

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Executive Summary

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Smart city technologies are increasingly empowering cities, utilities, and other local public agencies to improve the resiliency, efficiency, and transparency of services. In transportation, examples include mobile apps for integrated payment across public transportation services and on-demand microtransit with real-time schedules accessible to riders. However, there are gaps in existing indices for measuring the adoption of these technologies. Many indices use proprietary data, do not allow users to disaggregate subcomponents of the index, and provide limited tools for data visualization.

This project developed an innovative user-friendly web interface for local and state policymakers that tracks and displays information on the adoption of such technologies in California across the policing, transportation, and water and wastewater sectors for a comprehensive set of local service providers: connectedgov.berkeley.edu. Contrary to conventional smart city indices, our platform allows users to view rates of adoption in maps that attribute adoption to the local public agencies or service providers actually procuring or regulating the technologies in question. Users can construct indices or view technologies one by one. Users can also explore the relationship between technology adoption and local service area conditions and demographics, or download the raw data and scripts used to collect it.

To illustrate the utility of this approach, we analyze here a subset of the data we collected: information on the rollout of private sector smart city transportation technologies. We focused on the differential rollout of micro-mobility, transportation network companies (TNCs), and electric vehicle chargers across all cities in California. We 1) web scraped this data from vendor websites and produced replicable script to automate future data collection; 2) integrated this data into our interactive geospatial visualization tool, visible at connectedgov.berkeley.edu, and 3) analyzed patterns of adoption across the state to identify gaps in access for each technology.

Our analysis indicates that private technologies vary in their rollout across California. All technologies studied are most common in the largest cities in the Bay Area and LA, but while TNC access has spread to small cities surrounding the largest areas in the Bay Area/LA, EV charger and micro-mobility access remain concentrated in the largest cities. TNC and EV charger access is more common in areas with higher household incomes, while micro-mobility access is more likely to be found in places with a younger population. This analysis demonstrates the utility of web scraped data for detecting gaps in private technology service provision, particularly for smaller, rural, and lower-income jurisdictions.

For each studied technology, we also developed interactive maps in ArcGIS to display patterns of adoption. While many existing smart city indices do not allow users to disaggregate index components (such as the adoption of specific technologies), our maps allow users to view each technology separately and create their own comparisons. In addition, we developed dashboards to allow users to explore whether adoption is associated with local demographic conditions, such as urbanization and median household income. We hope this tool will be useful both for citizens looking to understand technology access in their own jurisdiction, as well as agencies and policymakers hoping to address gaps in service provision across the state.

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Introduction

The term “smart city” technology is generally used to describe technical systems that deploy information and communication technologies (ICT) to improve the efficiency, transparency, or performance of urban services and infrastructure (e.g., Chourabi et al. 2012). They typically draw on new types of data, such as data collected through video feeds, sensors, or crowd-sourced information from individuals. Examples include smart parking apps, which allow users to view available spaces and provide integrated payment solutions, and smart flow meters, which allow consumers to track water usage and monitor service interruptions in real time. These technologies are growing in popularity due to their potential to address service and infrastructure challenges at the local level. Existing research highlights the comparative benefits and costs of smart technology adoption, including user concerns over privacy, equity and access, and public safety, and benefits for service delivery and transparency (Chorubai 2012; Shaheen and Cohen 2016; Taeihagh and Lim 2019). Literature debates the positive and negative effects for inequalities and justice (Meíjer and Rodriguez Bolivar 2016). For example, transportation network company services were originally primarily accessible for wealthier, highly educated populations in urban areas (Clewlow and Mishra 2017; Alemi et al 2018). Cybersecurity and data privacy concerns also pose barriers to adoption across sectors, as consumer data transmitted from Internet of Things (IoT) devices is stored in centralized agency databases (Kitchin and Dodge 2011).

To-date, there is no comprehensive data on the adoption or rollout of smart city technologies at the local level, even though such data would inform policymaker efforts to understand the implications of the smart cities trend and decide whether or not to support the adoption of specific technologies. There are a number of existing indices currently available to track technology adoption but, as we explain below, all have major drawbacks that limit their usefulness. Our research project developed an interactive platform displaying data on the prevalence of smart city technologies across local jurisdictions in California that will provide policymakers with crucial background as they work to retain the state’s position as a center for innovation and complement existing state-wide efforts to aggregate data. State-level policymakers can use our platform to monitor which local agencies are adopting or permitting utilization of various technologies. They can identify leading agencies from which others can learn, laggard agencies in need of technical assistance or nudges, and conditions that may explain patterns of adoption. They can also use the data to determine whether transportation leads or lags other sectors in the state with respect to technology adoption. Our project also provides the empirical data necessary to understand what factors are conducive to the adoption of these technologies, and what factors appear to militate against adoption. Local policymakers can use the data to identify agencies that have already navigated the procurement or implementation process, from which they could seek advice.

During the 2019-2020 academic year, we developed a methodology for collecting data on the adoption of smart city technologies for a comprehensive set of local service providers in California (Frick et al. 2021). We track each technology according to the local jurisdiction or service provider that would be the most likely to procure or regulate the technology in question. Currently, our platform provides information on smart technologies used in the transportation and policing sectors that: a) captures new, leading technologies adopted by just a few innovative jurisdictions as well as technologies that have already diffused quite widely; and b) helps local public agencies achieve a range of different objectives, including resilience, transparency, and cost savings. We utilize the technique of webscraping—writing code to automatically capture data stored on public websites or in apps—to regularly monitor the adoption and continuing use of these "public-facing" technologies by local agencies. We plan to complement webscraping with surveys of local public agencies—administered in partnership with statewide membership associations—to capture the adoption of technologies not visible on the web, which will allow us to collect data on water and wastewater technologies as well.

Limitations of Existing Smart City Indices

We are not the first researchers to track the proliferation of smart city technologies. A growing number of research efforts compare cities in terms of their level of "smartness." Some of these initiatives are based in academic disciplines such as urban studies, political science, and city and regional planning. Others are spearheaded by think tanks or private consultancies. These efforts have generally culminated in smart city indices that rank cities according to composite scores. For example, some projects compare cities on the basis of indicators of progress, including competitiveness, access to ICT and transportation, natural resources, and quality of life (Kitchin 2011; Escolar et al. 2019). Some focus on measures of broader concepts, such as sustainability and public safety. Yet others focus on the adoption of specific technologies related to public services like smart parking and electronic health reporting (Giffinger 2010; Neirotti et al. 2014). In sum, existing smart city indices vary significantly in what aspects of "smartness" are being tracked—i.e., technology adoption or indicators of broader goals like sustainability or equity. Most do not include fine-grained data regarding the adoption of specific technologies, a focus that would be very useful for local public agencies concerned with making decisions about technology adoption or state policymakers keen to incentivize the adoption of specific technologies.

In this section, we review existing smart city indices, highlighting whether or not they possess a number of important types of data and analytic tools that could enable policymakers to use them to evaluate and/or incentivize technology adoption. In particular, we evaluate these indices according to whether or not they:

- Contain disaggregated adoption information for a large set of specific technologies
- Are comprehensive in coverage within a particular geographic area
- Attribute technology adoption to the variety of local service providers who actually engage in technology adoption (special districts, utilities, etc. as well as cities) rather than just cities
- Provide transparency regarding data sources and index construction, and open access to the data itself
- Offer modular presentations of data on an open access website, allowing users to choose different pieces of data to display, and the exact format in which the data is displayed.

The *McKinsey Global Institute (MGI) Smart Cities Report* compares cities on the basis of their utilization of a very comprehensive set of smart city technologies, yet is limited in geographic scope (MGI 2018). The MGI index focuses specifically on ICT applications across 50 large cities around the world. Their index is broad in coverage, encompassing eight sectors, including policing, healthcare, water and wastewater, energy, and transportation. The data is also quite fine-grained within each sector: cities are scored based on the presence of specific applications (e.g., real time air quality information, smart parking, smart streetlights). According to the report and associated website, data was collected through searches of city government websites, vendor websites, and online media searches, with cities receiving a score from 0 – 1 capturing non-adoption, limited/pilot rollout, and full adoption. Yet the exact sources for particular pieces of information is not provided. Moreover, users of the website cannot configure displays of the data. While the report (in PDF format), with descriptive charts comparing cities across different sectors, is available for download, the raw data that allows users to assess data quality and analyze patterns on their own is not.

The *Oliver Wyman Urban Mobility Readiness Index* scores cities on the basis of broad aspirational categories: infrastructure (i.e., road quality, rail networks), social impact, systems efficiency, market attractiveness, and innovation (Oliver Wyman 2019). Some of its key indicators include the presence of specific smart city technologies (for example EV charging stations, traffic flow management infrastructure, etc.). The index indicates every city's ranking on each of the five indicators, which are comprised of subcategories, for example "diversification of public transit nodes," "cycling adoption," and "supply chain efficiency." Each of these performance indicator categories are weighted, as determined through consultation with academic and policy experts in urban planning, mobility technology, and traffic management, and the UC Institute for Transportation Studies. While the index allows users to view scores for each of the five broad categories, the methodology used and data for specific subcategories is unavailable to the public. It is also unclear what data sources were drawn upon for each indicator. Coverage is also limited to 50 large cities worldwide, rather than the broader set of local jurisdictions that would be making decisions to procure smart city technologies of different types. The web presentation of this index is more interactive than some; the website allows users to group cities by different country characteristics (i.e., Gross Domestic Product (GDP) per capita, geographic area) to visualize variations between background conditions and smart city scores and view individual cities' scores across sectors in comparison to the average. However, one cannot assemble and display a different index than the one already provided.

The *IESE Cities in Motion Index*, developed by the Center for Globalization and Strategy and the Department of Strategy at the University of Navarra in Spain, provides data on specific sectors in an interactive and user-friendly geospatial format. The index ranks 165 large global cities according to nine broad criteria, including governance, environment, mobility and transportation, and human capital (see Figure 1). Each city receives a specific score for each of the nine categories. The nine indices are comprised of aggregated data from 101 indicators sourced from public databases. For example, the World Bank Strength of Legal Rights Index and United Nations E-Government Development Index are two components of the "Governance" category. In contrast, for "Mobility & Transportation," the index draws upon data regarding the uptake of specific technologies. Users can view individual scores for each category either in a visual or tabular format. IESE also publishes a complete list of public data sources used to generate the nine indices, and units of measurement for each (e.g., Solid Waste—measured as the total amount of municipal waste per person in a year). Although the aggregated/cleaned index data is not available, IESE provides links to the original sources for each indicator. While the index is broader than most in its geographic coverage, and a model in terms of the configurability and transparency of the data, it does not provide information about the adoption of specific smart city technologies, and only offers scores for cities rather than other local public agencies.

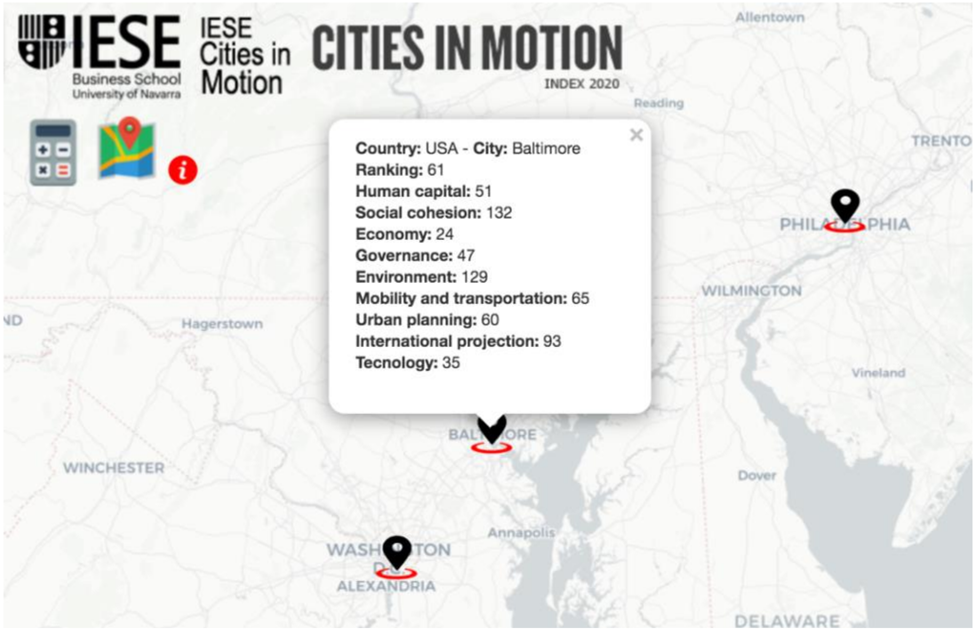


Figure 1. IESE Cities in Motion Web Interface

Araral 2020 constructs an index that draws data on smart city technology adoption collected through a survey conducted by the International City/County Management Association (ICMA). It has been disseminated through an article published in a scholarly journal rather than through a website. The survey was administered to a representative sample of 329 municipalities in the United States, meaning that it captured a far broader range of cities than the other indices we reviewed—though it still only covers a small fraction of municipalities in the United States (Araral 2020). For each of these municipalities, the survey covered smart city technologies in 13 different areas, including civic engagement, smart payments and finance, waste management, and telecommunications. Its focus on municipalities, as in the cases above, means that technologies principally adopted by municipalities are included, but technologies that have been adopted by other public agencies—such as transit agencies or water districts—are not captured. A 2020 report drawing on this data includes an index ranking each city based on its score for the 13 areas but does not ask respondents about the adoption of specific technologies within a sector. Rather, survey respondents are asked to select a "stage of adoption" for an aggregated set of smart city technologies in each sector. The data is proprietary and only available for purchase, so survey responses are not available to the public for download.

We also reviewed smart city indices compiled by other entities, including the consultancy Roland Berger, the Institute for Management Development (IMD), Kearney, and Nierotti (Nierotti et al. 2014; Henzelmann 2019; Kearney 2020; IMD 2020). The IMD index surveys consumers regarding satisfaction with existing technology rather than tracking adoption. Both Kearney and Roland Berger are proprietary indices; data is not available to the public. The Kearney index is broad and focuses on general indicators rather than specific technologies. While the Roland Berger index has a higher level of specificity, it does not contain a transparent list of included technologies (Henzelmann 2019). Finally, while Nierotti et al. (2014) develops an index using publicly available data from ICT vendor websites, research centers, and existing rankings, it focuses on broader sectors rather than tracking the adoption of specific technologies.

In sum, existing smart city indices vary in terms of the extent to which they track the adoption of specific technologies as opposed to progress towards a range of social, environmental, and governance criteria. All focus on cities rather than other types of local public agencies that may procure such technologies. None are comprehensive in geographic coverage within a particular country or state. None make their raw data publicly accessible. And only a few allow users to view the underlying data used to create indices and/or assemble their own indicators, as opposed to simply viewing pre-set indices. (In Table 1, we indicate this variation by differentiating between "decomposable" indices and those that are "not decomposable".)

Table 1. Limitations of Existing Smart City Indices

Index	Scope	Specificity		Unit of Analysis	Modularity	Open Data
		Technology	Categories			
McKinsey Global Index	50 cities worldwide	Technology Specific	Broad (8 sectors)	Cities	Not decomposable	No
Oliver Wyman Mobility Index	50 cities worldwide	Partial	5 categories, 56 sub-categories	Cities	Decomposable	No
IESE	165 cities worldwide	Partial	Broad (9 sectors)	Cities	Decomposable	Yes
Araral 2020	329 U.S. cities		Broad (13 sectors)	Cities	Not decomposable	No
Roland Berger	87 cities worldwide	No	Broad (12 categories)	Cities	Not decomposable	No
IMD Smart Cities Index	109 cities worldwide	Yes	Broad (5 categories)	Cities	Not decomposable	No
Kearney Global Cities Report	50 cities worldwide	No	Broad (5 categories)	Cities	Not decomposable	No
Nierotti et al 2014	70 cities worldwide	No	6 sectors, 28 sub-categories	Cities	Not decomposable	Yes

Our Approach to Collecting, Presenting, and Sharing Data

While informative, the smart city indices reviewed above are not ideal for important constituencies in California we hope to serve through our project. These include:

- *Local public agencies* and private service providers interested in exploring the possibility of adopting new technologies, and learning from peers as they do so;
- *State-level policymakers* concerned with meeting conservation, efficiency, and transparency goals through technology adoption;
- Stakeholders in *regional associations* interested in understanding the technology leaders and laggards within their region, as well as how their region compares with others;
- *Researchers* interested in smart city technology adoption and its drivers;
- *Citizens* interested in how their local service providers compare with those in neighboring jurisdictions, as well as services available in their area.

The low coverage rates of existing indices within the state, the fact that many do not track the adoption of specific technologies, the tendency to attribute all technology adoption to municipal governments, and the fact that users cannot manipulate or download the data make them less than ideal for policymakers at multiple tiers of government. For this reason, we have structured our data collection and presentation initiative so that it addresses these gaps. We collect data on specific technology applications, and attribute technology adoption to the jurisdictions or service providers most likely to procure or regulate the technology in question for a comprehensive set of service providers in the California transportation, policing, and water and wastewater sectors. On our recently released connectedgov.berkeley.edu platform, we present this data in a modular format that allows users to select different combinations of technologies in a geospatial display and provides open-access data for public download. This section elaborates on each of these points. A summary of the list of specific technologies surveyed and data collection methods is given in the Appendix below.

Tracking specific technologies: In contrast with some of the indices above, our data collection effort and web interface provide information on the adoption of specific technologies. We leave it to users to decide whether or not these technologies meet particular public purposes. This is important, given current debates over the costs and benefits of specific smart city technologies, particularly in the policing sector. It also allows policymakers to explore the factors associated with adoption of particular technologies, as the barriers to adoption likely vary substantially across technologies.

Attribution of technology adoption: Most existing indices (if not all) track technology adoption by cities. We attribute adoption to the jurisdiction most responsible for a given application—e.g., water agencies for smart irrigation incentives—to better understand jurisdictions' rationale for adoption as well as barriers to adoption. This makes our data relevant to local policymakers, agencies, and regional initiatives in a given sector, as technology adoption is displayed based on the primary agencies which manage the adoption process. It also allows individuals to click on their location on a map and see the variety of agencies that provide services in their location, and the technologies that have been adopted by each.

To identify key technologies we should monitor, accurately attribute technology adoption to the correct jurisdiction, and design our website to support the goals of policymakers, we consulted with experts in the fields of transportation and water and wastewater. For transportation technologies, we consulted with Alexandre Bayen, the director of the UC Berkeley Institute for Transportation Studies (ITS), and Karen Trapenberg Frick at the UC Berkeley Department of City and Regional Planning. We conducted additional background research based on ITS and Connected Corridors background reports and policy papers to survey existing expertise (Kurzhanskiy and Varaiya 2015; Spiller et al. 2017; Shaheen and Cohen 2018; Deakin et al. 2020). The results of this research for transportation technologies are displayed in Table 2. For the water and wastewater sector, the Bay Area Council, Association of California Water Agencies, and members of the Soga Research Group at the University of California, Berkeley provided feedback on our list of technologies and relevant level of analysis. For policing, attribution was easier as policing technologies are generally adopted by city police departments and county sheriff's departments.

Table 2. Transportation Technologies by Jurisdiction

Cities	Transportation Agencies
EV Chargers	Real time fleet management
Transportation Network Companies	Integrated transit payment
Micro-mobility	Advanced Traffic management
Ramp metering	Geofencing
Smart Parking	Bus service rerouting after system disruption
Transit Signal Priority	
E-hailing	
Intelligent Traffic Signals	
Demand based microtransit	
Smart Pavement management	
Predictive maintenance	
Smart parcel lockers	
Construction mapping	

Comprehensiveness: In contrast to existing smart city indices, our data collection effort chooses depth over breadth: we are collecting data for the full set of service providers in our three sectors within the state of California. This allows us to capture the entire range of cases—jurisdictions or service providers that are the earliest to adopt new technologies, and those that have been much less likely to do so. The comprehensive information generated through this exercise provides a better information base for state-level policymakers considering whether to provide incentives or other types of support.

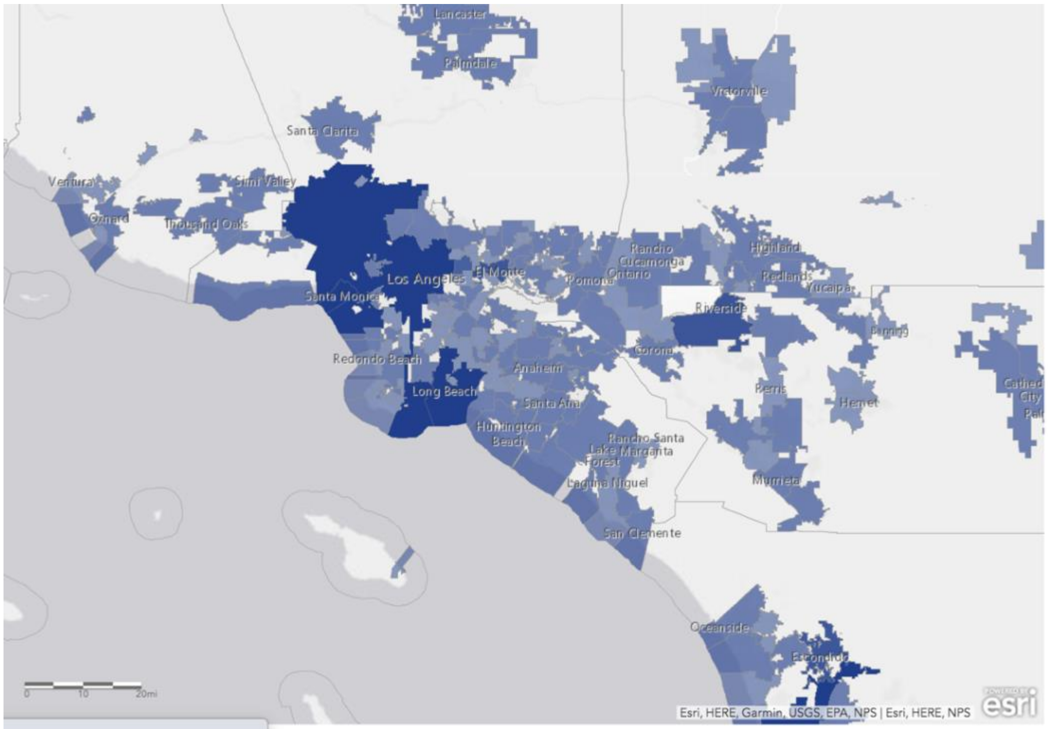
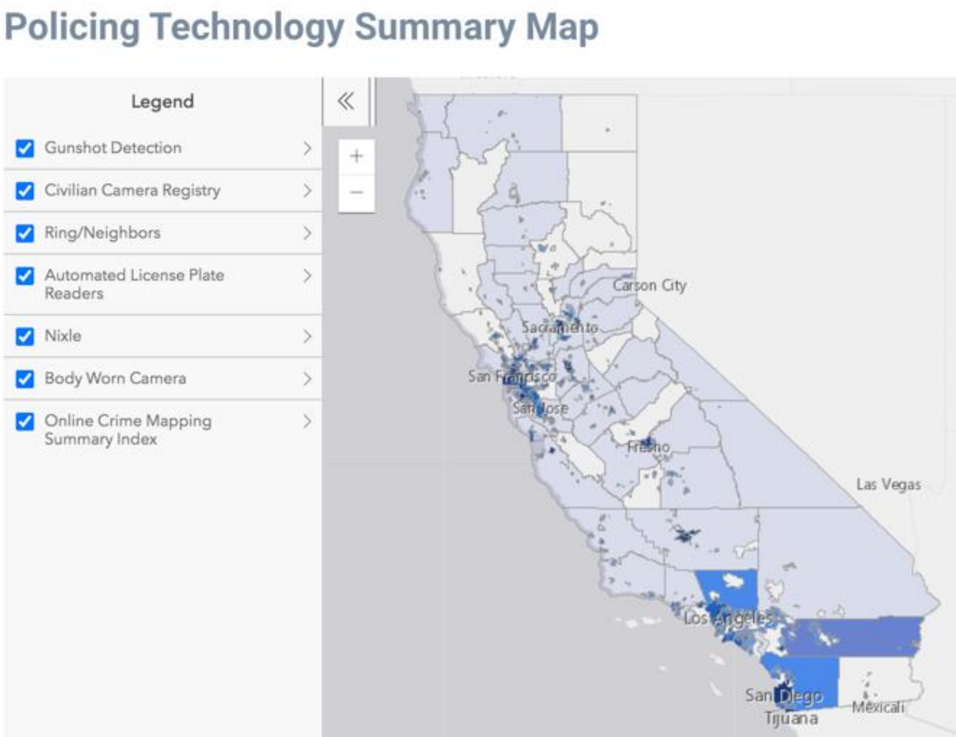


Figure 2. Variation in Transportation Technology Adoption in Los Angeles Area

Note: This figure displays the adoption of EV chargers, micro-mobility, and Uber in the Los Angeles Area. Darker colors represent a greater number of technologies present in a given city. On our web platform, individuals can choose which technologies they would like to display. This data is current as of May 2021.

An interactive and flexible display: Contrary to most existing index projects, which provide users with a single index or set of rankings, we have developed a public interface (connectedgov.berkeley.edu) to display data on technology adoption in a geospatial and modular format that allows users to select any combination of technologies on the map in a given sector (for examples see Figure 2 and Figure 3). Many indices present city-sector level rankings in PDF format, which means viewers are not able to construct comparisons of different sectors across or within a city. In contrast, we have developed interactive base maps using ArcGIS to create a visual index of technology adoption for each city in California, for both policing and transportation sectors. These base maps allow users to select individual technologies to view on the map one at a time, or together—with a color gradient indicating which jurisdictions have adopted more technologies than others. This enables users to choose which technologies should figure in their own index of technology, rather than accepting an existing index hierarchy. While other available indices provide disaggregated scores for each city, they do not allow users to interactively compare different combinations of technologies on a digital map. Our platform allows users to select any combination of technologies in a given jurisdiction. Following the completion of our surveys in the water and wastewater, and transportation sectors, we will add more transportation technologies and create a new set of maps focused specifically on water and wastewater. In later versions, we also intend to allow users to assign their own weights to particular technologies.



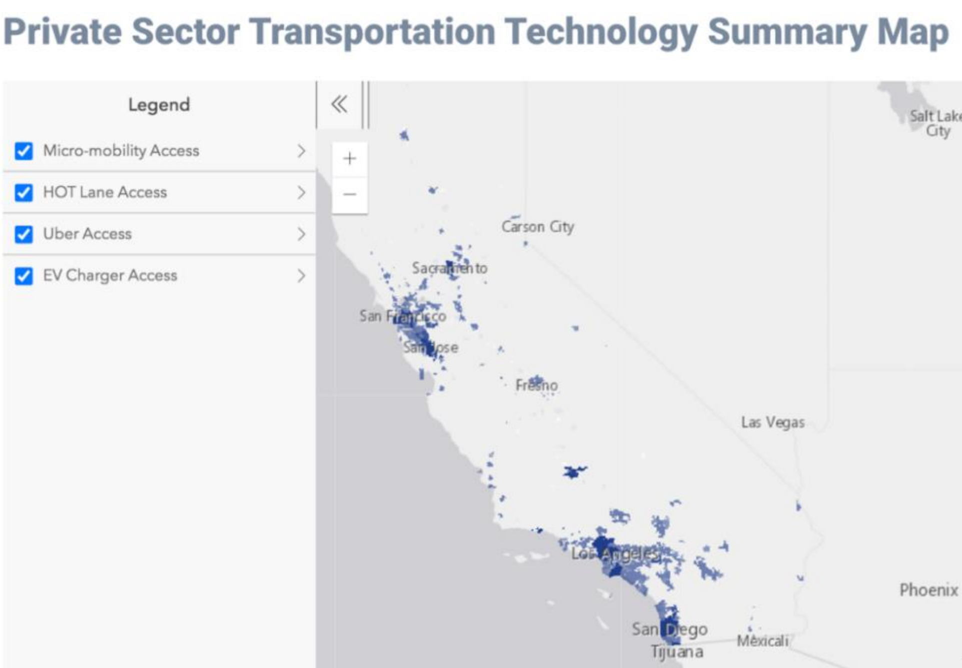


Figure 3. Sectoral Maps of Transportation and Policing

Note: The above figures display our sectoral maps of policing and transportation technology adoption respectively. The layer list indicates the technologies included on each map. Darker colors on the map represent a greater number of technologies present in each jurisdiction.

Exploring determinants of technology adoption: Our web platform also includes interactive ArcGIS dashboards that display correlations between technology adoption and factors that may be associated with technology adoption or rollout, such as urbanization, median household income, and the crime rate. The dashboards automatically update to reflect the geographic area displayed on the map. For example, our policing dashboards display correlations between violent crime rate and median household income, and access to crime mapping, civilian camera registry, text message public security alerts (issued by Nixle, the most popular provider), automated license plate readers, Ring/Neighbors partnerships, and body-worn camera technology. The display from our dashboard captured in Figure 4, for example, shows that adoption of the Nixle security alerts is highest in medium-income areas and lowest in low-income areas, and that adoption is highest in areas with medium crime rates and lowest in high-crime areas.

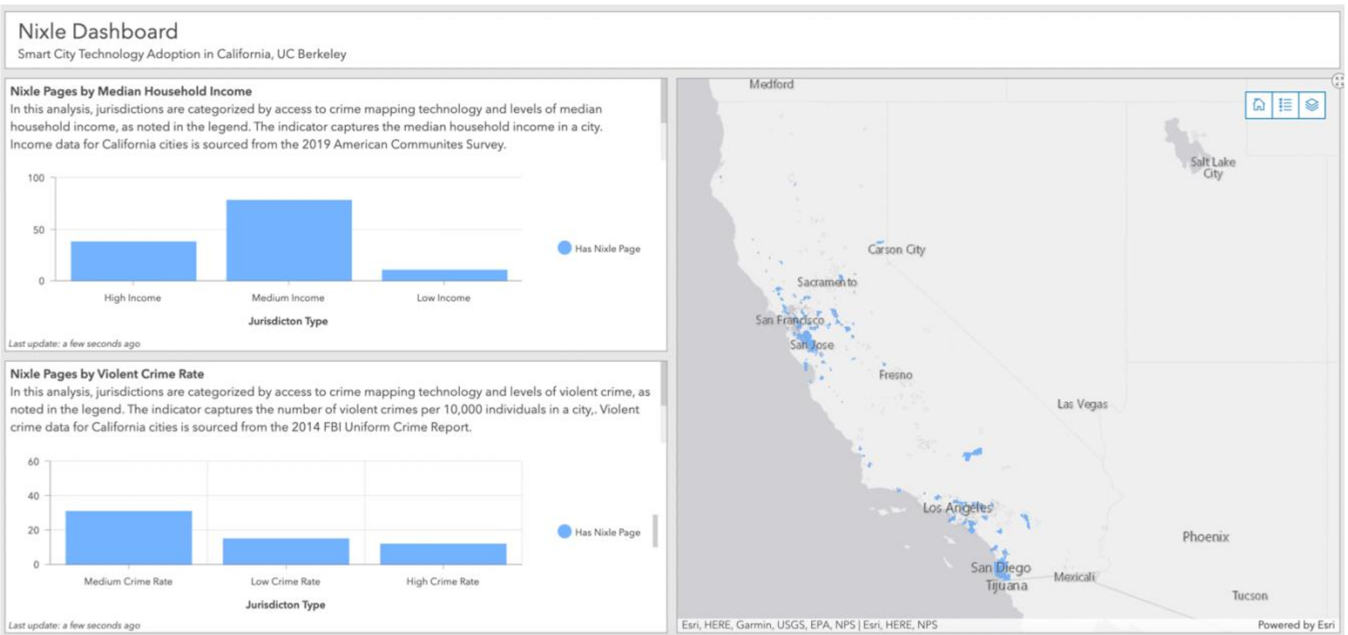


Figure 4. **Nixle Alert Adoption by Violent Crime Rate and Income (May 2021)**

Making our data publicly accessible: A third key contribution from our research is that our data is also available for public download, with replication scripts available that scrape data from vendor websites in Python. Our webscraping scripts allow users to download and clean the data for EV charging access, micro-mobility, and transportation network company access. We also include scripts that replicate our empirical analyses and descriptive figures in R, as well as creating the maps presented in ArcGIS through Python Jupyter notebooks. This open-source approach provides users with both an option to download raw data, replication scripts, and additional documentation on when and how the data was collected. While other indices typically do not allow users to download raw data for each jurisdiction, our open-source approach provides both data and collection methods in a publicly accessible and replicable format.

Overall, our data collection effort and web interface (connectedgov.berkeley.edu) represent a more comprehensive and useful tool for policymakers because of these features.

Data Collection to Date

During the 2019-2020 academic year, we developed a methodology for collecting data on the adoption of smart city technologies for a comprehensive set of local service providers in California in the transportation, policing, and water and wastewater sectors. As described above, we are tracking each technology according to the local jurisdiction or service provider that would be the most likely to procure or regulate the technology in question. We first identified a set of technologies in transportation, policing, and water and wastewater that: a) captured new, leading technologies adopted by just a few innovative jurisdictions as well as technologies that had already diffused quite widely; and b) helped local public agencies achieve a range of different objectives, including resilience, transparency, and cost savings. We utilized webscraping—writing code to automatically capture data stored on public websites or in apps—to regularly monitor the adoption and continuing use of "public-facing" technologies by local agencies. During 2019-2020 and 2020-2021, we compiled data for a variety of transportation and policing applications. We incorporated additional data from the Electronic Frontier Foundation's *Atlas of Surveillance*. Table 3 details the technologies for which we were able to collect data for all relevant local service providers in California. More detail on how data was collected for each of these technologies is included in the Appendix to this report.

Table 3. Data Collected To-Date

Policing Applications	Transportation Applications
Body-worn cameras	GTFS feeds (static and real-time)
Disaster early warning systems	HOT lanes
Security alerts	Electric vehicle chargers
Gunshot detection	Micro-mobility services (scooters, bikes)
Predictive policing	Ridesharing services
Automated license plate readers	
Crime mapping	
Drones	
Civilian camera registries	
Facial recognition systems	
Ring/Neighbors partnerships	

We are currently working to expand the technologies covered to those that are not visible through the web or apps, focusing on water and wastewater, and transportation. (For a list of technologies that we plan to cover, see Appendix Table A1.) This will allow us to incorporate a complementary set of technologies affecting internal operations that are oriented towards improving efficiency, mitigating environmental impacts, and improving health standards. We will collect these data through surveys of the local public agencies that decide whether or not to adopt the technology in question. This approach will enable us to collect more detailed data, including more information about levels of rollout or implementation (i.e., piloting, partial vs. full deployment) and barriers to adoption (e.g., costs, human capital constraints, procurement difficulties, concerns about reputational risks). Our team and others can use these data to identify specific adoption barriers and compare levels of diffusion across California agencies for a more comprehensive set of technologies. Our surveys will be administered in collaboration with state-wide associations that bring together service providers within the transportation and water and wastewater sectors.

Illustration of the Utility of our Data and Visualization Tools: The Rollout of “Private” Transportation Technologies

This section outlines the ways in which the data being collected can be used to understand patterns of adoption in smart city technologies that are typically operated by private firms in the transportation sector. Many studies on such private sector transportation technologies focus on a single technology or on a small number of cities in a given area. There is little research comparing the adoption of multiple technologies across a comprehensive set of cities in a large geographic area. This section examines the characteristics of jurisdictions with access to EV chargers, micro-mobility (e.g., scooter and bike rentals),[1] and TNC services, commonly known as ridesharing services (e.g., Uber and Lyft) for all 482 municipalities in California. These three technologies are primarily deployed by private firms but are affected by local regulations and adopted in the context of government-funded incentives, for example to increase access in low-income communities. Learning about patterns of adoption will highlight variation in access between different types of jurisdictions, the ways in which different smart city transportation technologies have diffused in the state, and identify factors that enable rollout. It also allows us to uncover variation across and within regions which will increase understanding of issues of equitable access across income and geographic areas.

Our analytic approach builds upon existing research, which explores the extent to which demographic factors such as wealth, resident age, and environmental attitudes help explain variation in the adoption of these technologies. Our study goes further than existing studies in its use of data for a comprehensive set of cities in a particular state, our inclusion of variables measuring voters’ political preferences, and the analysis of multiple technologies in tandem.

Our analysis finds that the largest cities in the Bay Area and Los Angeles have the highest access to all three technologies. However, while all large and small cities in the Bay and LA have Uber access, only half of smaller cities have above-median EV charger access and just two have access to micro-mobility services. Technology access also varies across income, with higher-income jurisdictions more likely to have EV chargers and Uber access. In contrast, micro-mobility access does not vary with median household income in a city. The analysis also indicates that Uber access tends to be higher in places with strong public support for transportation expenditures and micro-mobility access is greater in areas with higher public transportation ridership. Overall, our analysis shows that these private sector technologies have not been adopted uniformly by California, with Uber and EV charging concentrated in the Bay Area and LA, and micro-mobility access more prevalent in larger than smaller cities across the state.

[1] Micro-mobility refers to shared lightweight vehicles including scooters and bikes offered by the vendors Lime, Jump, Lyft, Wheels, Spin, Scoot, and Bird.

Data for the Study

In our analysis, we analyze variation in the rollout of smart city transportation technologies operated by private firms in California cities in 2021. To do so, we utilized web scraped and publicly available data. Our analysis covers the total sample of 482 California municipalities. This data is current as of May 2021. We exclude counties and unincorporated territories because municipalities are the primary jurisdictions regulating these technologies.

Outcome Variables

Data on the number of electric vehicle chargers in each city was obtained from the Department of Energy and cross referenced with web scraped data from Charge Hub for completeness. Data on the presence of micro-mobility services in California cities was collected from the websites of each provider operating in the state (details in Appendix below). Data on TNC services indicates whether or not a city has Uber access, and we web scraped the list of cities covered from the vendor website.[2]

Explanatory Variables

We collected data on a number of features of each city's population that might help explain why some cities have access to certain smart technologies while other do not (see Table 4). We first obtained data on city size and location to compile a list of principal cities—the largest city in a Metropolitan Statistical Area (MSA)—and additional cities meeting employment and education requirements from the 2019 American Communities Survey (ACS) (US Census Bureau 2019). This data on principal cities, together with a list of city members in the Association of Bay Area Governments and Southern California Association of Governments, was used to create our jurisdiction indicator.[3] The indicator categorizes cities as "Principal Cities in the Bay Area/LA," "Member Cities in the Bay/LA," "Principal Cities in Minor MSAs," or "Other." In our models, we compare rates of access between principal cities in the Bay Area or Los Angeles metropolitan region, other cities in these two regions, principal cities in other metropolitan areas in the state, and small cities outside the Bay Area and Los Angeles. Data on median household income, population density, population age and public transportation usage, was obtained from the 2019 ACS. Finally, we calculated the percentage of the population in each city in the top 20 percent of the California income bracket.

To capture political partisanship at the city level, we included data on the ratio of votes for the Democratic candidate to total votes in the 2020 presidential election. City level voting data was downloaded from MIT Election Lab. The analysis also included voting data for two California ballot measures: initiative Proposition 6 and bond measure Proposition 68, which measure public support for transportation spending and support for the environment respectively. Data on the ratio of yes votes to total votes in each city was obtained for both

[2] Uber data is easier to interpret than Lyft data, and was the primary focus of our study for this reason.
[3] We define the Bay Area as the counties within the Association of Bay Area Governments (ABAG): Alameda, Contra Costa, Marin, Napa, San Mateo, Santa Clara, Solano, Sonoma, and the city and county of San Francisco. We define Los Angeles as the counties of the Southern California Association of Governments (SCAG): Imperial, Los Angeles, Orange, Riverside, San Bernardino, and Ventura.

propositions from the California Secretary of State. These data were joined by location with the American Communities Survey variables and other data using the names of each city.

Table 4. Definitions And Descriptive Statistics for Outcome and Other Variables

Outcome Variables	Definition	N available	Mean	Min	Max
EV Chargers (total)	Total count of EV chargers in a jurisdiction	482	69.42	0	3697
EV Chargers per capita	Number of electric chargers in a city divided by population	482	0.0015	0	0.108
EV Chargers per capita: median threshold	Threshold of EV charging access per capita by the California median (5.7 chargers per 10,000 people). Jurisdictions with higher than the median are coded as 1; 0 otherwise.	482	0.5	0	1
Micro-mobility	Indicator (0/1) for private sector micro-mobility service coverage	482	0.029	0	1
TNCs	Indicator (0/1) for Uber service coverage	482	0.741	0	1
Explanatory Variables	**Definition**	**N available**	**Mean**	**Min**	**Max**
Jurisdiction Indicators: Principal City Bay Area / LA	Indicator for Principal Cities in LA and Bay Area MSAs	482	0.109	0	1
MSA Member City Bay Area/LA	Indicator for MSA Member City in the Bay Area and LA	482	0.495	0	1
Principal City Minor MSA	Indicator for Principal Cities in minor MSAs	482	.0788	0	1
Income Level	Log of the median household income in a city	481	11.21	10.12	12.429
Population density	Population in a given city divided by geographic area	482	4318	26.14	23193
Age	Population between 20-30 years of age (micro-mobility and TNC access) Population over 55 (EV charging)	482 482	0.138 .280	.0037 .091	0.329 .963
Public transit usage	Percent of workers that use public transit to commute to work	482	.034	0	.362
Proposition 68 Voting	Ratio of votes in support of Prop. 68 bond measure on the environment to total votes	482	0.561	0.293	0.905
Proposition 6 Voting	Ratio of votes rejecting Prop. 6 ballot initiative repealing SB 1 to total votes	482	0.5601	0.263	0.913
Democratic electorate	Percent Democrat vote share in a given city for the 2020 presidential election	481	.62	.18	.96
Wealthy population	Percent population in CA's highest income quintile	478	47.94	38.72	75.83

We conduct separate analyses for the rollout of each technology (EV charging, micro-mobility, TNCs) using ordinary least squares regression (OLS); analyses of correlations between the above explanatory factors and outcome variables are reported in the next sections. Overall, we find that EV charging access is highest in principal cities in the Bay Area/Los Angeles and smaller metropolitan statistical areas (MSA), and that access is lower in smaller cities surrounding San Francisco and Los Angeles. And that EV charging access is also highest in high-income areas. In contrast, micro-mobility access is highest in middle income areas, and in principal cities in the Bay Area/LA. Similarly, Uber access is greater in the Bay Area and Los Angeles metropolitan regions than elsewhere in the state.

The Differential Rollout of Electric Vehicle Chargers

What predicts relatively high numbers of EV chargers per capita in a given municipality? To examine varying levels of EV charging infrastructure, we focus on two main measures. We first examine the number of EV chargers per capita. This is captured by the total number of Level 2 chargers and Tesla superchargers listed in a city divided by the city's population. Second, we examine whether or not cities possess more total chargers per capita than the median value for the state (5.7 chargers per 10,000 people). Cities with lower than the state median are coded as "0" for "low access" and cities with EV access per capita above the median are coded as "1" for "high access." Prior studies have shown that EV charger access tends to be greater in higher-income communities, and areas with older, Democratic residents (Carley et al., 2013; Farkas et al., 2018; Hsu and Fingerman 2021). We therefore expect greater EV charger access in areas with a higher median household income, Democratic vote share, fraction of the city population comprised by households in California's top income quintile, and in larger cities, particularly in the Bay Area and Los Angeles metropolitan areas. We also include a measure of pro-environmental sentiment among voters: support for Proposition 68, a state bond measure to support environmental initiatives.

Our first set of models (1-3) in Table 5 shows the community-level factors associated with the presence of above-median levels of EV chargers. The results indicate that EV chargers are more often present at above-median levels in the largest (principal) cities of the two largest metropolitan regions in the state (the Bay Area and Los Angeles regions) than in small cities outside these regions. In these largest cities in the Bay Area and LA, 45 cities (85%) have a higher level of EV charger access than the state median. A second set of models (4 and 5) examine factors associated with the number of EV chargers per capita (rather than above-median levels), and show that these principal cities are simply more likely to have above-median levels of chargers; they do not have more chargers per capita than the other types of cities we examine. Meanwhile, smaller cities in the Bay Area and Los Angeles Metropolitan Area are less likely to possess both above-median numbers of chargers per capita, and more chargers per capita, than other cities in the state. These differences across jurisdictions can also be viewed through our interactive web platform (see Figure 5, bottom panel).

Table 5. Predictors of Electric Vehicle Charger Access by CA Cities (May 2021)

	Dependent variable:				
	EV threshold			**EV chargers per capita**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Principal City Bay/LA	0.219***	0.239***		0.00001	-0.0001
	(0.078)	(0.077)		(0.0003)	(0.0003)
Member City Bay Area/LA	-0.168***	-0.139***		-0.001***	-0.001***
	(0.054)	(0.052)		(0.0002)	(0.0002)
Principal City Minor MSA	0.028	0.041		-0.0004	-0.0004
	(0.083)	(0.082)		(0.0003)	(0.0003)
Pop. Density			-0.00002**		
			(0.00001)		
Log Median HHI	0.091*	0.122**	0.121**	0.0005**	0.0004
	(0.055)	(0.054)	(0.055)	(0.0002)	(0.0002)
Percent over age 55	0.885***	0.825***	0.450*	0.003**	0.003***
	(0.259)	(0.255)	(0.266)	(0.001)	(0.001)
Prop. 68 Vote Ratio	0.822***		-0.280	0.001	0.003***
	(0.150)		(0.404)	(0.002)	(0.001)
Democrat Vote Share		1.063***	1.558***	0.003	
		(0.176)	(0.486)	(0.002)	
Top quintile	0.019***	0.016***	0.017***	0.0001***	0.0001***
	(0.005)	(0.006)	(0.006)	(0.00002)	(0.00002)
Constant	-2.155***	-2.416***	-2.406***	-0.010***	-0.010***
	(0.632)	(0.628)	(0.623)	(0.003)	(0.003)
Observations	477	477	477	475	475
R^2	0.212	0.222	0.176	0.158	0.154
Adjusted R^2	0.200	0.210	0.166	0.144	0.141
Residual Std. Error	0.448 (df = 469)	0.445 (df = 469)	0.457 (df = 470)	0.002 (df = 466)	0.002 (df = 467)
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$		

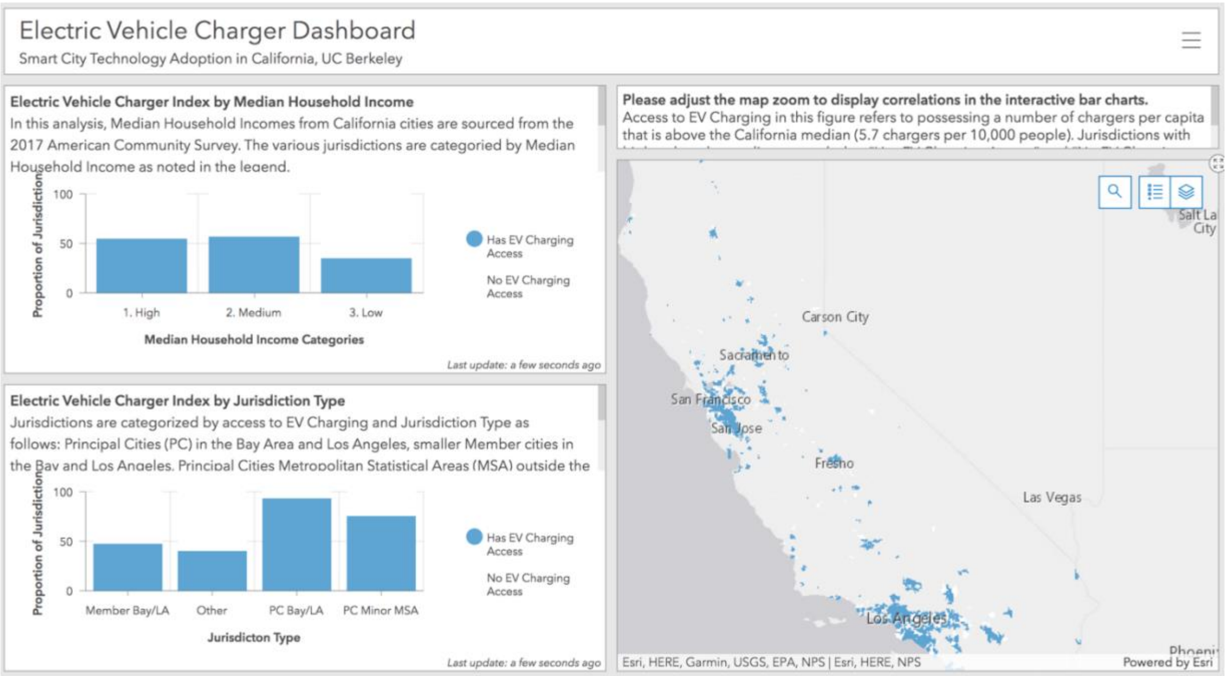


Figure 5. EV Charger Access by Income and Jurisdiction Type (May 2021)

Note: This figure is a screenshot of the interactive dashboard displaying EV charger access and correlations between median household income and urbanization. Data is current as of May 2021.

The most striking results from the data analysis summarized in Table 5 indicate that EV chargers have been installed at higher rates in areas with concentrated wealth. There are more EV chargers per capita and higher rates of above-median access in cities where a larger proportion of income comes from California's top income quintile. Out of the 129 cities with the most concentrated wealth (where over half of the total household income comes from households in the top 20 percent statewide), 92 cities (71.3%) have higher EV charger access than the state median. Our data analysis also shows that cities with higher median household income are more likely to have above-median EV charger access, though not more chargers per capita (see also Figure 5, top panel). This fits with the existing literature, which finds that greater levels of homeownership and median household income are positively correlated with EV charger access in urban neighborhoods (Hsu and Fingerman 2021).

We also find that cities with larger proportions of older, Democratic residents are more likely to have an above-median level of EV charging access and more EV chargers per capita. This finding is also consistent with prior work, which finds EV ownership to be more common in wealthier, older, and more environmentally conscious communities (Carley et al., 2013; Farkas et al., 2018; Hsu and Fingerman 2021). Prior work has shown that disadvantaged communities have lower rates of both EV ownership and charger access, and EV owners within these communities typically have higher educational attainment and income than average residents (Canepa et al. 2019). Controlling for these factors, Black and Latinx populations have lower charger access than other groups. Our analysis of charger access goes further than existing work by incorporating political characteristics of populations with higher levels of charger access, including Democratic vote share, age, and urbanization. Future research should explore racial and wealth inequalities in EV charging access, and policies providing for EV rebates for low-income communities.

The Differential Rollout of Micro-Mobility Services

Where are micro-mobility companies choosing to operate in California? To document variation in the penetration of micro-mobility services, we examine a binary indicator (0/1) reflecting whether or not services are offered in a particular city, drawn from each vendors' list of cities in their service area maps. A city is assigned a score of 1 if there are one or more micro-mobility vendors that provide services. We use OLS regressions to examine the relationship between city characteristics and the presence or absence of micro-mobility services in all California cities. We hypothesized that a number of factors would be associated with the presence of micro-mobility services: being a large city in a major metropolitan area, a relatively young population (that would own cars at lower rates), and high rates of public transit usage. Prior work has shown that micro-mobility services are used by young commuters as a substitute for intracity public transit (Lazarus 2020; Liao and Corriera 2020). We also included community demographic characteristics such as population density and median household income in our models, as well as Democratic vote share and support for Proposition 6 (which would have reduced state public transportation funding). While existing studies focus on micro-mobility adoption and usage in specific metropolitan areas like Washington D.C. and New York City, our analysis covers the entire state of California, including cities in both urban and rural regions.

Our results, presented in Table 6 and the bottom panel in Figure 6 (from our interactive web platform), show that micro-mobility access is in fact highest in the largest cities in the Bay Area and LA, and in the largest cities of smaller MSAs. Models 1 and 2 include variables reflecting whether or not cities fall in the Bay Area or Los Angeles, and whether or not a city is a principal (large) city within its region. These models indicate that micro-mobility vendors operate in seven of the 53 largest cities (13.2%) in the Bay Area and LA and four of the largest cities in MSAs outside the Bay Area and LA (10.5%). In comparison, only two smaller cities in the Bay Area and Los Angeles possess micro-mobility. Micro-mobility is more strongly concentrated in the largest urban jurisdictions than TNC access, notably even large cities in more rural parts of the state. Substituting a population density variable for these city-location indicators (Models 3-4) suggests that these differences are not driven by differences in population density across these different types of cities; there is no statistically significant relationship between density and the presence of micro-mobility services.

Table 6. Predictors of Micro-mobility Access by CA Cities (May 2021)

	Dependent variable: Micro-mobility Index			
	(1)	(2)	(3)	(4)
Principal City Bay/LA	0.073***	0.070**		
	(0.028)	(0.027)		
Principal City Minor MSA	0.085***	0.085***		
	(0.028)	(0.028)		
Member City Bay Area/LA	-0.016	-0.022		
	(0.020)	(0.018)		
Pop. Density			0.00000	0.00000
			(0.00000)	(0.00000)
Median HHI	0.011	0.012	0.014	0.010
	(0.020)	(0.020)	(0.019)	(0.019)
Percent between Age 24-35	0.736***	0.706***	0.911***	0.887***
	(0.199)	(0.196)	(0.205)	(0.205)
Public Transit Usage	0.753***	0.804***	0.679***	0.782***
	(0.184)	(0.175)	(0.188)	(0.180)
Democratic Vote Share	-0.034	0.059	-0.128	0.056
	(0.117)	(0.057)	(0.118)	(0.060)
Prop. 6 Vote Ratio	0.129		0.254*	
	(0.142)		(0.139)	
Constant	-0.281	-0.269	-0.339	-0.272
	(0.237)	(0.236)	(0.228)	(0.226)
Observations	481	481	481	481
R^2	0.171	0.169	0.130	0.124
Adjusted R^2	0.157	0.157	0.119	0.115
Residual Std. Error	0.155 (df = 472)	0.154 (df = 473)	0.158 (df = 474)	0.158 (df = 475)
Note:			*p<0.1; **p<0.05; ***p<0.01	

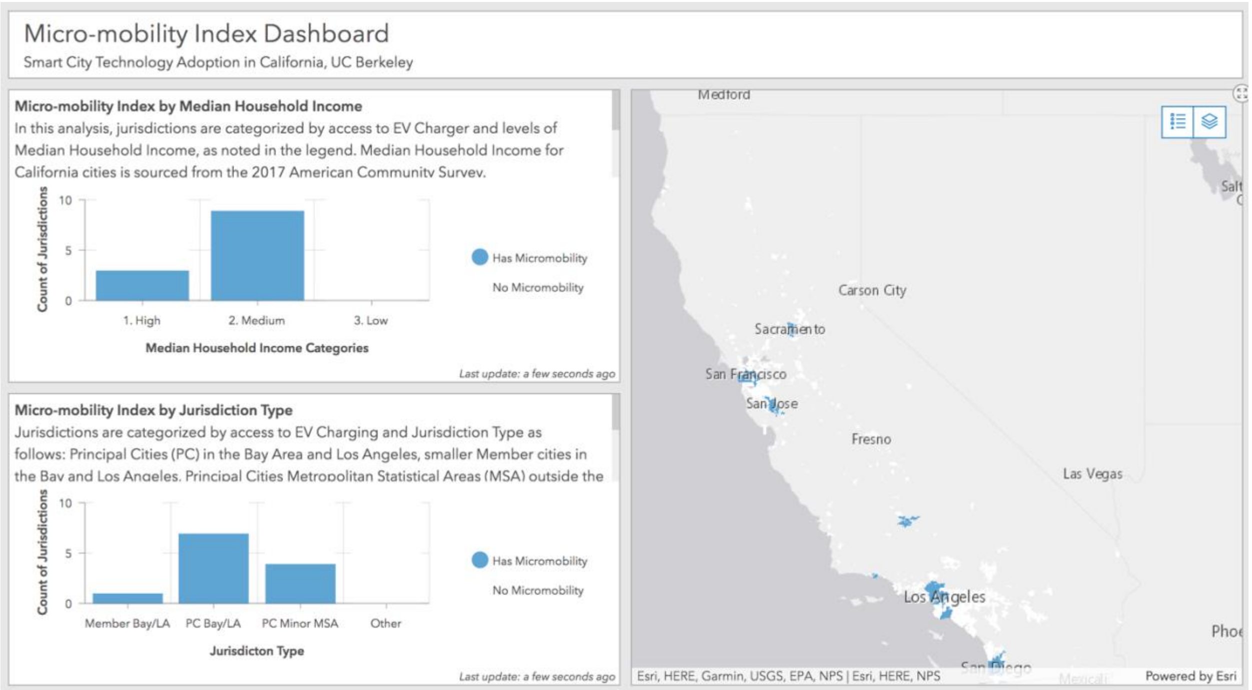


Figure 6. Micro-mobility Rollout by Income and Jurisdiction Type (May 2021)

Our analysis also shows that micro-mobility is not more prevalent in high-income communities (see Table 6, Figure 6 top panel). Rather, as we expected, firms are more likely to operate in cities with larger fractions of young adults and higher rates of public transit usage. This suggests that micro-mobility is most used by young adults for commuting purposes in major urban areas in conjunction with public transit, but not necessarily in higher income areas. This finding is complementary with other work, which suggests that micro-mobility is primarily used for short trips (11-15 minutes) and commuting between major public transit stops (Lazarus 2020). Particularly during times of high congestion, micro-mobility is a faster and more efficient alternative to ridesharing and public transportation and can alleviate traffic congestion (McKenzie 2020). While micro-mobility was originally rolled out in high-income urban areas, more recently firms have introduced dockless ridesharing in middle- and low-income urban communities, where it has served as a substitute for car ownership (Liao and Corriera 2020).

Our results are in line with existing studies highlighting the synergies between micro-mobility and public transportation ridership, as micro-mobility addresses first and last mile coverage. They may be explained, at least in part, by the fact that some cities have partnered with micro-mobility vendors to offer reduced transit fares in key transportation corridors—for example around airports and major business districts—and have even integrated micro-mobility into trip planning applications for a seamless user interface (Shaheen and Cohen 2018; Shaheen and Cohen 2020). This is important for low-income communities with low rates of car ownership, as micro-mobility provides last mile services to regular public transit users. Cities and vendors have worked together to increase public transit accessibility and micro-mobility use, rather than in competition.

The Differential Rollout of Transportation Network Company Services

Where are Transportation Network Companies offering services in California? Where are their services unavailable? To document these patterns, we scraped data from the Uber website for service coverage throughout the state. From this data, we constructed a binary indicator reflecting whether or not Uber operates in each city in the state. We used OLS regressions to examine the relationship between city characteristics and the presence or absence of Uber services in all California cities.

Similar to micro-mobility, we hypothesized that a number of factors would be associated with the presence of TNC services in a city: being a large city in a major metropolitan area, a relatively young population (with low rates of car ownership), and a high-income population. We also considered whether or not public transit usage is correlated with TNC services, as existing studies have yielded mixed results. Prior work has shown that TNC services are used by young commuters as a complement to intracity public transit (Murphy 2016; Liao and Corriera 2020). However, others find that ride-hailing replaces trips that would have been made by driving, carpooling, and public transportation, and incentivizes users to take a greater number of trips overall (Clewlow and Mishra 2017). Uber and Lyft users also report that they reduced their public transportation use once ridesharing became available. Our analysis therefore includes a measure of public transportation ridership and a measure of support for Proposition 6 (which would have reduced state public transportation funding) to capture the relationship between Uber access and community attitudes towards public funding for transportation. We also included community demographic characteristics such as population density and median household income in our models, as well as Democratic vote share in the 2020 presidential election. These variables allow us to describe the various demographic characteristics of cities in conjunction with community support for public transportation.

Our analysis, presented in Table 7 and in the bottom panel of Figure 7, indicates that Uber is present at greater rates in the Bay Area and Los Angeles metropolitan regions than elsewhere in the state. This contrasts with micro-mobility and EV charging access, which are both more accessible in the largest Bay Area/LA cities relative to smaller surrounding cities. All small cities in the Bay and LA have Uber access, while 30 percent of large cities in other parts of the state do not. Uber is also more likely to be present in the largest cities in minor MSAs relative to small cities in minor MSAs.

Table 7. Predictors of Uber Access by CA Cities (May 2021)

	Dependent Variable: Uber Indicator			
	(1)	**(2)**	**(3)**	**(4)**
Principal City Bay/LA	0.530***	0.529***		
	(0.049)	(0.049)		
Member City Bay Area/LA	0.515***	0.518***		
	(0.035)	(0.035)		
Principal City Minor MSA	0.104**	0.102**		
	(0.050)	(0.050)		
Pop. Density			0.00002***	0.00003***
			(0.00001)	(0.00001)
Median HHI	0.138***	0.145***	0.365***	0.395***
	(0.034)	(0.033)	(0.037)	(0.042)
Democratic Vote Share	1.697***	1.647***	2.657***	0.575***
	(0.216)	(0.205)	(0.253)	(0.138)
Percent Between Age 24-35	0.108		0.464***	0.130
	(0.145)		(0.176)	(0.188)
Prop. 6 Vote Ratio	-1.752***	-1.696***	-2.728***	
	(0.261)	(0.249)	(0.287)	
Public Transit Usage	0.196	0.176		-0.398
	(0.324)	(0.323)		(0.411)
Constant	-1.247***	-1.297***	-3.713***	-4.205***
	(0.367)	(0.361)	(0.392)	(0.446)
Observations	481	481	481	481
R^2	0.609	0.608	0.426	0.318
Adjusted R^2	0.602	0.602	0.420	0.311
Residual Std. Error	0.276 (df = 472)	0.276 (df = 473)	0.334 (df = 475)	0.364 (df = 475)

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

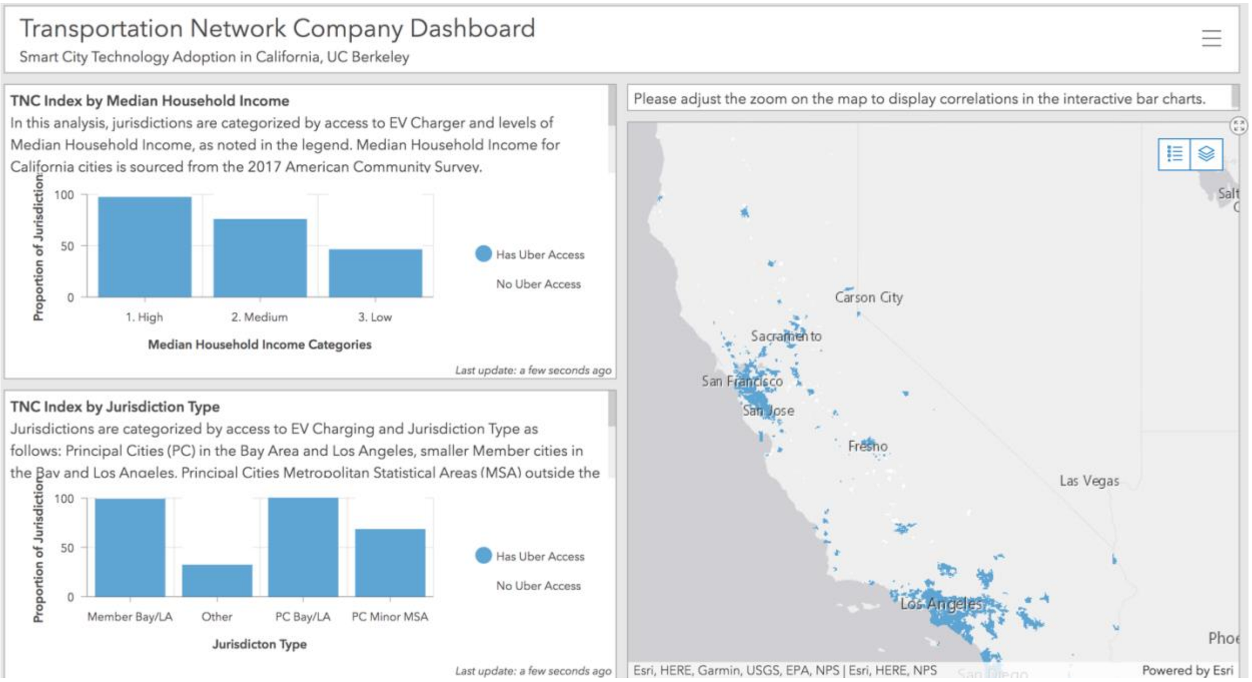


Figure 7. TNC Adoption by Income and Jurisdiction Type (May 2021)

We also find that Uber is more likely to offer services in high-income jurisdictions (Table 7, Figure 7 top panel). Cities with a higher median household income are more likely to have Uber access. Our findings complement the existing literature, which indicates that TNC usage is higher amongst wealthy, urban, and educated populations (Gherke 2020). The existing literature finds that in suburban areas, communities with more educated populations and low car ownership utilize Uber most frequently. Across seven metro regions, a third of the population age 18-29 used Uber compared to only four percent of the population 65 and over. Wealthy college age use was double that of lower income and less educated residents (Clewlow and Mishra 2017). Households that use Uber also tend to have fewer children and lower rates of car ownership (Feigon and Murphy 2018). Education is also positively correlated with TNC usage, as well as high levels of employment (Gherke et al. 2019; Alemi 2018a; Alemi 2018b). These studies broadly suggest that TNCs are most widely used by young, working adults with high levels of educational attainment, but few children and low car ownership. While we find that Uber is more likely to operate in higher income communities, in contrast to existing literature we find no relationship between ridership and the percentage of city population comprised by young adults or the rate of public transit utilization for California cities.

Our data analysis also indicates that cities with Democratic majorities are more likely to have Uber access. Uber access is positively correlated with a higher percentage of the population that voted Democratic in the 2020 presidential election. Results suggest that TNCs are used by cities with larger, wealthier, Democratic populations in California, and that access has spread to suburbs outside the largest cities in the Bay Area and

LA. This complements earlier studies which focused on earlier stages of Uber adoption, and suggests that Uber ridership is expanding to smaller metropolitan areas in California.

We also find that California cities with low rates of support for public spending on transportation are more likely to have Uber access. Uber is more likely to operate in cities in which a majority of voters supported Proposition 6, which would have repealed SB-1 (funding statewide transportation infrastructure upgrades). This contrasts with some existing studies, which indicate that TNC services are a substitute for private vehicle ownership in areas of high urban density and during periods of high congestion like rush hour (Erhardt 2019; McKenzie 2020). However, these studies focus primarily on metropolitan areas, while our analysis includes both large and small cities across California. Indeed, other research suggests that in wealthy urban areas, particularly in childless households, TNC services can lead to transit ridership reduction as wealthier residents substitute Uber for public transportation (Wenzel 2021). One study also found that Uber and Lyft serve as substitutes for public bus systems during hours of peak demand, particularly among wealthy urban households (Grahn et al. 2020).

In order to expand TNC access to low-income communities and integrate usage with existing public transportation infrastructure, cities are partnering with TNC vendors. For example, San Diego and Summit, New Jersey have partnered with ridesharing services within a geofenced area, providing complimentary rides to public transit hubs during peak commute hours (Shaheen and Cohen 2020). As of fall 2019, twenty-nine cities and transit agencies in California offer subsidized shared mobility to elderly, disabled, and low-income adults (Deakin et al. 2020). Many of these programs help agencies reduce the cost of service in low density areas and during times of low usage, while providing timely assistance to communities in need. While many of these programs are in the pilot stage or early phases of deployment, ridesharing companies and cities are partnering in a variety of ways to incentivize carpooling, shared mobility, and access to low-income communities in areas of limited public access.

Stepping back, our analysis of the rollout of smart city transportation technologies by private firms across California highlights some common patterns as well key differences. We find that all three types of technologies examined—EV chargers, micro-mobility, and TNC services—are present at a greater rate in the largest cities in the San Francisco Bay and Los Angeles metropolitan regions than elsewhere in the state. EV chargers and Uber services are more prevalent in wealthier cities, while micro-mobility is primarily associated with higher percentages of 24 to 35-year-olds. These findings indicate that cities and the state could further encourage the deployment of these technology-enabled services in areas with substantial lower-income populations and lower rates of access to public transit, building upon existing initiatives.

Expected Impact from this Project

California has long been a hub of technological and environmental innovation, due in no small part to the prominence and influence of Silicon Valley innovation and California's tendency to adopt environmental regulations earlier than the federal government. Will California retain its edge, particularly as the state faces climate change, aging infrastructure, wildfires, and other threats?

The deployment of smart city technologies offers California the opportunity to retain its technical edge while also addressing pressing environmental challenges, concerns about government transparency, and rising costs. Publishing GTFS (General Transit Feed Specification) feeds, for example, makes it easier to use public transit, and may improve ridership numbers. The adoption of gunshot detection technology may enable police departments to direct patrolling efforts more effectively, and thereby improve pedestrian safety. This logic led a variety of actors to propose the "Water Innovation Act" (SB-351) this February, which would incentivize technology investment.

We have developed an interactive platform displaying data on the prevalence of smart city technologies across local jurisdictions in California. We designed the platform (www.connectedgov.berkeley.edu) so that it would serve as a more useful tool for policymakers at the state and local levels than existing smart city indices. It covers all relevant local jurisdictions within the state of California, records the presence or adoption of specific technologies (rather than simply progress toward meeting broad goals like sustainability), covers multiple sectors, allows users to view and configure the data according to their own interests and purposes, and provides open access to our raw data.

The data we have collected thus far through webscraping, as well as this innovative display format, should provide policymakers with crucial background information as they work to retain the state's position as a center for innovation, and complement existing state-wide efforts to aggregate data. State-level policymakers can use our platform to monitor which local agencies are adopting or permitting utilization of various technologies. They can identify leading agencies from which others can learn, laggard agencies in need of technical assistance or nudges, and conditions that may explain patterns of adoption. Our inclusion of policing and water and wastewater alongside transportation will allow state officials to see if transportation is a leading or lagging sector, and also to track policing technologies that may encourage or discourage various modes of transportation. Local policymakers can use the data to identify agencies that have already navigated the procurement or implementation process, from which they could seek advice.

This report also contains an illustration of the types of analyses one can perform with the data we are collecting. The preceding section analyzed the rollout of "private" smart city technologies in the transportation sector within California, focusing specifically on EV chargers, micro-mobility services, and Transportation Network Company services. We find that rates of deployment have been much higher in the state's major metropolitan areas than outside of them—a pattern that makes perfect sense given the larger markets and network effects in these regions. However, ride-sharing services and micro-mobility could potentially address gaps in public transit services more effectively if they are rolled out to more of the state. Relatedly, as the price of electric vehicles continues to decrease, adequate charging infrastructure will be needed in less affluent jurisdictions for EVs to be viable forms of transportation throughout the state. The afore-mentioned new state initiatives offer promising support for such expansion.

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Appendix: Summary of Technology Applications and Data Collection Efforts

This appendix summarizes our data collection to-date and describes data collection we plan to conduct in the future. Table A1 lists the technologies for which we plan to collect data. This list was developed in consultation with experts in the policing, transportation, and water and wastewater sectors. Our aim was to include a subset of the smart city technologies utilized in each sector that captured both very new technologies, as well as those that had diffused to a greater extent. We also deliberately chose technologies that ranged in terms of their purpose (e.g., conservation, cost-savings, transparency, etc.). Technologies which we have already collected through webscraping and other online sources appear in bold. We plan to collect information about the adoption of the remaining technologies through surveys of local service providers.

Table A1. Technologies Slated for Data Collection by Sector

Policing	Transportation	Water and Wastewater
Body Worn Cameras	HOT Lanes	Water quality mapping
Automated License Plate Readers	GTFS	Leak detection: Satellite
Crime Mapping	EV Chargers	Pipe replacement: AI and predictive analytics solutions
Nixle Alerts	Transportation Network Company Access	Leak detection: Wireless pressure sensors
Gunshot Detection	Micro-mobility	Emergency response mapping
Civilian Camera Registry	Ramp metering	Smart irrigation incentives
Drones	Smart Parking	Smart flow meters
Real Time Crime Centers	Real time fleet management	Smart water metering
Predictive Policing	Transit Signal Priority	Remote employee data entry
Facial Recognition	Autonomous Vehicles	Acoustic flow measurement
Ring/Neighbors Partnership	Integrated transit payment	Construction mapping
Video Analytics	E-hailing	SCADA systems
	Intelligent Traffic Signals	Acoustic pressure monitoring
	Demand based microtransit	Household water leak detection
	Advanced Traffic management	
	Smart Pavement management	
	Pay as you go insurance	
	Geofencing	
	Predictive maintenance	
	Bus service rerouting after system disruption	
	Smart parcel lockers	

Below, we describe our progress to-date on collecting data on the applications listed in Table A1. So far we have collected comprehensive data on twelve policing technologies and six transportation technologies.

Transportation Technologies

HOT Lanes

One provider of data, collection complete.

We leveraged available geospatial data on HOT lane coverage from the California Department of Transportation (Caltrans) to identify cities through which HOT lanes pass. We have plotted this data on a base map delimiting city boundaries to identify which jurisdictions have HOT lane access. HOT lane data was updated by Caltrans in May 2021.

GTFS

Two main websites for feed compilation, data collection complete with scope to obtain more comprehensive sample.

The General Transit Feed Specification allows agencies to publish transit arrival and departure times as well as schedule updates through either static (GTFS-s) or real-time (GTFS-r) feeds. We collected data on whether or not each transportation agency in California publishes either or both feeds. Data on GTFS adoption was scraped from Open Mobility Data and Transit Land in May 2021. Open Mobility Data provides a comprehensive list of GTFS-s adoption but does not publish the date of adoption and does not have comprehensive coverage of GTFS-r based on comparison with Transit Land and the websites of 10 transportation providers. We therefore used Transit Land data to determine GTFS-r publication. We also used the Transit Land API to determine the start date and most current update for GTFS-s and GTFS-r publication, as this data is not available through Open Mobility Data. From this data, we determined that 101 agencies publish GTFS-s data, and 13 agencies publish GTFS-r data. However, GTFS-r data from Transit Land is not complete, and a next step is to cross reference this with updated information from the California Integrated Transit Project.

EV Chargers

Two main data repositories, data collection complete.

Data on electric vehicle chargers was obtained from the Department of Energy and cross referenced with web-scraped data from Charge Hub in March 2021 for completeness. Our data contains both the number of EV chargers in a city, and a threshold indicating which cities have over the median level of EV charging access of 5.7 chargers per 10,000 persons. Jurisdictions above this threshold are coded as “High EV Charging Access” and below this threshold are coded as “Low EV Charging Access.” This data was updated in January 2021 and will be updated at regular bi-annual intervals.

Transportation Network Company Access

Two main providers, data collection complete with scope for more comprehensive analysis.

Data on transportation network company services covers Uber and was web-scraped from the list of cities posted on the Uber website in March 2021. For cities that share names with counties in California (i.e., Fresno, San Diego, Orange County), Uber services cover the entire county area. We thus matched the list of cities listed by Uber with counties in California to identify smaller cities within Uber service boundaries. In our analysis, cities with Uber access are coded as 1 and 0 otherwise. We chose to scrape Uber as Lyft reported providing comprehensive coverage in California. Lyft coverage is difficult to interpret since despite reporting comprehensive coverage, it only displays a subset of cities on its service area list. We did scrape the list of cities specifically listed on Lyft's website as key service areas and will monitor reporting of their service coverage to clarify access to their service.

Micro-mobility

Seven main providers, data collection complete.

Data on micro-mobility was collected from the websites of each provider operating in California and contains data on whether or not a range of micro-mobility vendors operate in each California city. Data on the providers Lime and Bird were web-scraped from vendors' websites in March 2021. For the remaining vendors—Jump, Lyft, Wheels, Spin, and Scoot—we identified cities manually in March 2021 due to barriers to webscraping in proprietary websites. Bird and Lime serve the greatest number of jurisdictions, with both operating in seven cities. The remaining vendors each service one to three cities.

Policing Technologies

Crime Mapping

Three main providers, data collection complete.

Crime-mapping refers to the display of geo-located crime data to citizens by police departments (Figure A1). Police departments generally do not have proprietary software for this service, but rather contract out the service to a provider. This entails sharing their data with the provider. There are three major providers: CommunityCrimeMap.com, CrimeMapping.com, and SpotCrime.com. The first two, CommunityCrimeMap.com and CrimeMapping.com, are vendors that contract with police departments for a period of time to display data. SpotCrime.com is an open-source platform that publishes police department data free of charge. We were able to draw directly from each of these websites and automated a search for the jurisdictions in California in March 2021. We found that of the 387 police and sheriffs' departments in California, 65 utilize Community Crime Map, 64 utilize Crime Mapping, and 357 are listed on SpotCrime.com. Data has been updated through regular monitoring of these websites and also cross referenced with data from the Atlas of Surveillance.

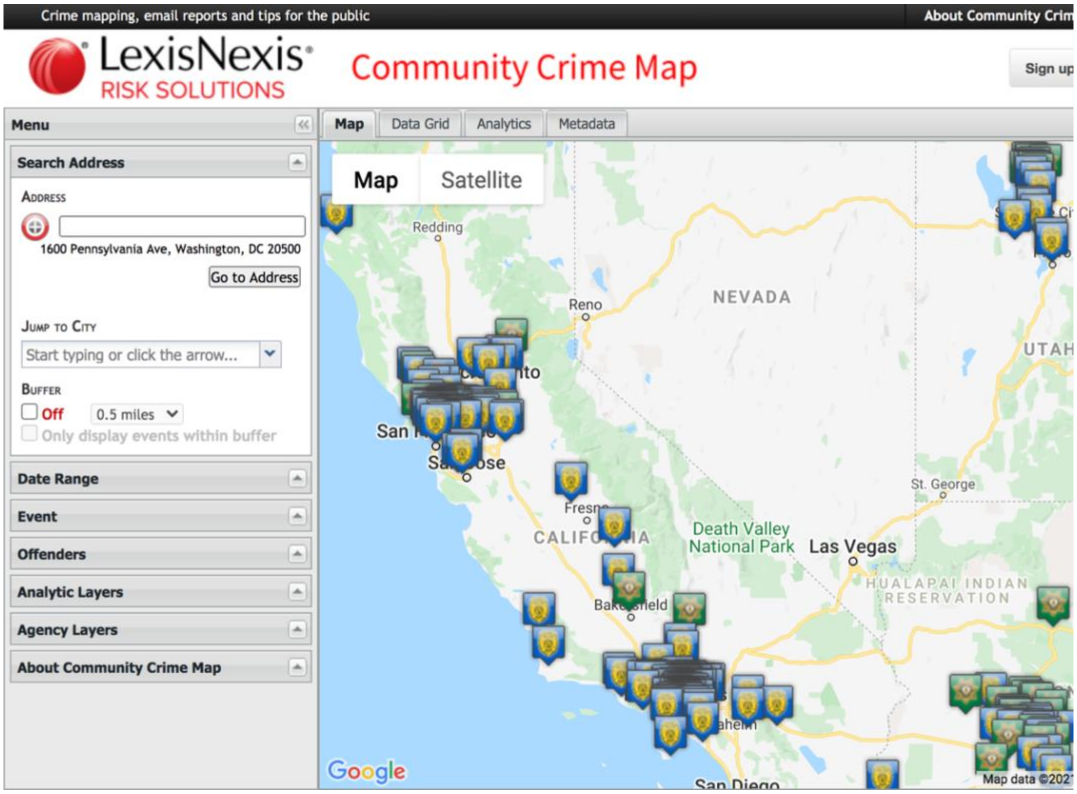

Figure A1. Community Crime Map

Nixle Alerts

One main provider; data collection complete

Service providers may want to send a variety of types of alerts over phone or email to citizens who opt into the service. Nixle allows public agencies to alert citizens of security threats through opt-in email and text notifications. Notifications are labelled "community," "advisory," and "alert." Community notifications include local events and successful police investigations, while advisory notifications include low-risk events like road closures or weather safety alerts. Advisory alerts pertain to missing children, violent crime, and other high-level emergencies. We web scraped Nixle adoption across the 328 police departments and 58 sheriffs' departments in California through an automated search of the Nixle website based on agency name. Figure A2 illustrates the distribution of alerts issued for each agency from the period May 2020—May 2021. The histogram illustrates that the vast majority of agencies with the Nixle platform issued fewer than ten notifications in the last year, and very few issued more than 40.

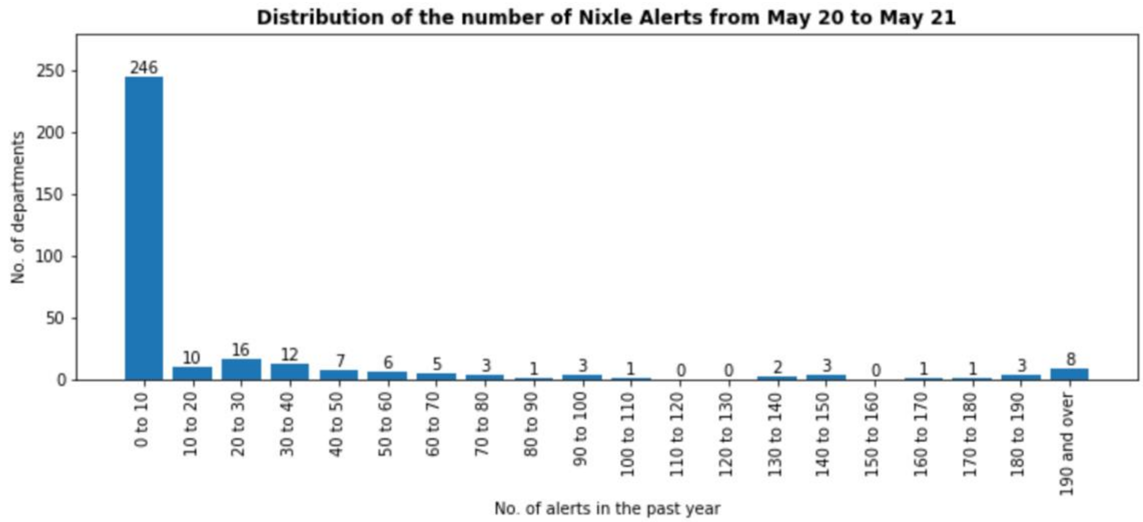

Figure A2. Distribution Nixle Alerts in CA Police Departments, May 2020 – 2021

Gunshot Detection

One main provider; data collection complete.

We web scraped the list of cities which have adopted ShotSpotter, the only gunshot detection equipment vendor, in May 2021. We additionally cross referenced this with data from the Atlas of Surveillance.

Data on the following technologies was obtained from the Atlas of Surveillance (compiled by the Electronic Frontier Foundation): Civilian Camera Registry, Drones, Real Time Crime Centers, Predictive Policing, Facial Recognition, Ring/Neighbors Partnerships, Video Analytics, Body Worn Cameras, Automated License Plate Readers, tracking adoption from 2013 to 2020.

The Atlas of Surveillance was a collaborative project led by the University of Nevada Reno Reynolds School of Journalism, with over 600 professors, students, and other researchers contributing data to the project. Data was collected with the crowdsourcing platform Report Back, which assigned volunteers a technology, location, and instructions on locating news articles, press releases, and official statements related to technology adoption. These links were then cross verified by researchers before addition to the dataset, which covers a total of 3,500 jurisdictions across twelve policing technologies.

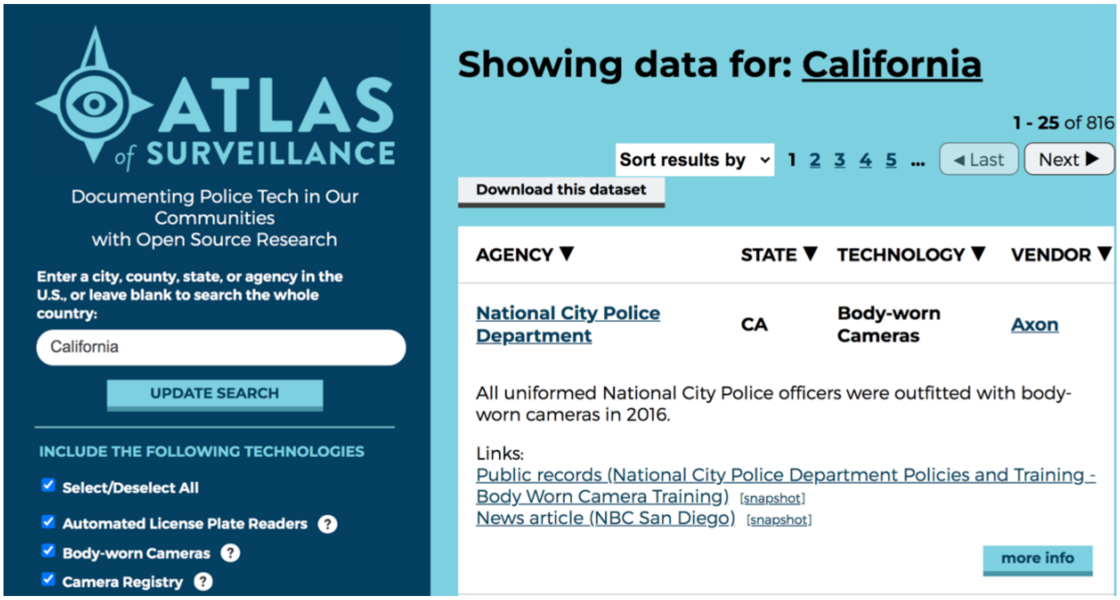

Figure A3. Atlas of Surveillance