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Using Context-Sensitive Criteria to Evaluate Local and Regional Transportation Policy: A Case Study on Cordon Pricing

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Using Context-Sensitive Criteria to Evaluate Local and Regional Transportation Policy: A Case Study on Cordon Pricing

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Dedication

For mom, thank you for all the futures you created for me.

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Abstract

Using Context-Sensitive Criteria to Evaluate Local and Regional Transportation Policy: A Case Study on Cordon Pricing

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As traffic congestion grows but existing roadway capacity remains fixed or limited, downtown congestion pricing offers potential as a tool to manage the transportation system. Though the idea is not new, congestion pricing has received a resurgence of attention in the United States in recent years because it could offer both congestion relief and transportation revenue. However, in order for a modern congestion pricing proposal to be politically feasible and publicly acceptable today it must be designed to offer more, such as equitable or progressive distribution of impacts, greenhouse gas emissions, and encouragement or support for alternate modes, including new mobility services.

In Seattle, serious consideration of the implementation of congestion pricing by 2021 is underway, and numerous policy questions remain open. One which many anticipate, particularly the public, is the question of where congestion pricing revenue would be spent. It is likely that at least some of the revenue will be allocated for transit, but where should service improvements be targeted, both geographically and demographically, so that mobility and access are not impaired, particularly for the already

transportation-disadvantaged, and so that multimodal travel is not just possible but preferable to driving? Could a regional partnership between transit agencies like Sound Transit and King County Metro and the City of Seattle secure transportation outcomes that align with both transit agencies' ambitious service expansion goals and Seattle's core equity, multimodal mobility, and climate goals?

This thesis seeks to answer these questions by using a mix of statistical models of transportation system level of service and individual-level mode choice. These models are used to predict how travelers across the region would change their travel behavior in response to cordon pricing in Center City Seattle under two investment scenarios. It is projected that investing in transit broadly across the region by decreasing transit service times produces transportation system outcomes that advance both local and regional strategic goals more than concentrated investment on downtown Seattle roadways and transit could advance Seattle's goals alone. Regional transit investment would decrease congestion more in Center City Seattle by improving transit access from outside Seattle into Center City, especially among neighborhoods with the lowest housing and transportation affordability, highest automobility, and highest transportation-related greenhouse gas emissions. Therefore, the findings strongly motivate that congestion pricing revenue in Seattle be spent on regional transit service improvement and expansion. Furthermore, the findings suggest that even regional transit investments that may not be directly linked to Center City will help to produce a mix of better transportation outcomes in Center City than concentrated investment would.

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Chapter 1: Introduction

LOCAL AND REGIONAL TRANSPORTATION CONTEXT

Transportation and mobility issues are the subject of constant attention in the Greater Seattle region. Seattle is known for some of the worst traffic congestion in the country – commuters spend the 6th most hours in traffic annually (INRIX, 2019). Circumstantial conditions only worsen matters. First, the Seattle economy is growing rapidly: a 2018 ranking named Seattle as the third-fastest growing large American city (McCann, 2018). Second, Seattle's downtown core, also known as the Center City, is about to meet the convergence of billions of dollars' worth of road and real estate construction, which will close many already-congested lanes. Meanwhile, light rail improvements which could provide relief will not arrive until 2021. City officials are doing what they can to notify the public of this so-called "Seattle Squeeze" from 2019 to 2024 by initiating public campaigns, outreach efforts, and traffic management measures to manage the anticipated congestion (Seattle Traffic, 2019). Because of the Seattle Squeeze and anticipated steady population and employment growth, 2017-elected Mayor Jenny Durkan and Seattle Department of Transportation (SDOT) anticipate Seattle Center City traffic to worsen over the next few years before planned improvements can provide congestion relief (Lindblom, 2018). This poses a major challenge for the city, as even when lanes reopen and light rail service begins, it must identify strategies to move people and goods through Center City more efficiently and reliably.

The City of Seattle also faces numerous transportation equity concerns and is committed to addressing them. Seattle has prioritized race and social justice citywide through the implementation of various municipal programs and policies over the last decade. One such program is Seattle's Transportation Equity Program, "created to provide safe, environmentally sustainable, accessible, and affordable transportation options that support communities of color, low-income communities, immigrant and refugee communities, people with disabilities, people experiencing homelessness or housing insecurity, LGTBQ people, women and girls, youth, and seniors to thrive in place in vibrant and healthy communities, and eliminate or mitigate racial disparities and the effects of displacement" by Seattle City Council Resolution 31773. Early outreach efforts by SDOT through this program have identified a mix of physical and digital barriers to transportation access, ranging from missing sidewalks, distant transit stops, and gaps in mobility-impaired accessibility to lacking access to online information about new projects, construction delays, transit options, and low-income program options. Transportation affordability or lack thereof is another barrier to transportation access in Seattle and the region; some have proposed strategies such as low-income transit passes but a major barrier is the lack of adequate funding to support such programs (Cohen, 2018). Furthermore, transportation affordability is linked to the region's housing affordability crisis. Home prices have risen almost 60 percent in the last decade, which is three times the national growth rate. Nearly 40 percent of middle-income households report they are cost-burdened by housing (Challenge Seattle, 2019). Affordable transportation options could enable more people to live where they wish to more comfortably.

Seattle also has a history of climate action. In 2011, the Mayor and City Council adopted a goal for the city to become carbon neutral by 2050 and published its first Climate Action Plan in 2013. In 2018, the city published a new Climate Action Plan reaffirming their commitment to a zero emissions future, and the first under Mayor Durkan. Transportation sector emissions reductions will play a major role in whether or not the city will achieve its goals; a recent greenhouse gas inventory found that 66 percent of Seattle's core emissions came from road transportation. Half of emissions were from passenger vehicles and the other half from freight. One strategy that Seattle hopes will help reduce transportation sector emissions is encouraging multimodal and active transportation choices over single occupancy vehicle trips through transit investment and improvements (City of Seattle, 2018). Additionally, the city published their New Mobility Playbook in 2017, outlining a vision for the transportation system that incorporates shared mobility and ridesourcing equitably and sustainably by advancing multimodal travel behavior (Seattle DOT, 2017).

These and other transportation issues underlie the five core values outlined in Seattle's current strategic transportation plan: safety, interconnectivity, vibrancy, affordability, and innovation. Some of the goals the strategic plan identifies to uphold these values include: reducing the percent of Seattle residents who drive alone to work in order to reduce congestion and greenhouse gas emissions; increasing the percentage of households within a 10-minute walk of a frequent transit route running every 10 minutes or better; and expanding multimodal travel options for low-income residents (Seattle DOT, 2015).

Beyond Seattle, a major regional transportation goal is transit service expansion. Sound Transit and King County Metro are two major transit providers in the Greater Seattle region (primarily light rail and various bus routes), each with visions of system expansion. Sound Transit is in its third phase of voter-approved capital investments called Sound Transit 3 (ST3), with goals to expand its existing system five-fold to realize a 116-mile light rail network with more than 80 stations serving 16 cities (Sound Transit, 2017). However, these ambitious plans are subject to a suite of financial risks. Tax revenue provides for the majority of Sound Transit's anticipated revenue over the next 40 years, and will be instrumental in financing the significant planned system expansions. However, a reduction in local tax revenues due to stagnant economic growth or revenue growth that falls short of the current forecast could threaten not only Sound Transit's ability to finance various projects but also their credit and ability to sell and finance long-term debt. As a result, a diverse and robust portfolio of funding sources for Sound Transit can reduce their financial risk and help them achieve their expansion goals.

King County Metro has also committed to system expansion in the coming decades, and it is one of the eight strategic goals named in their most recent strategic plan. They plan to "address the growing need for transportation services and facilities through the county" by expanding services and coordinating and developing services and facilities with other providers. In their most recent long-range transportation plan, Metro Connects, they specify some of the investments they plan to make, including frequent service for 73 percent of King County residents, a growing network of express buses, more local service, and coordination with other agencies and cities to create an interconnected transit system (King County Metro, 2015).

There is a long history of partnership between Seattle Department of Transportation and regional actors like Sound Transit and King County Metro to coordinate planning decisions in Center City Seattle. The 2016 One Center City plan included the three aforementioned agencies, the non-profit Downtown Seattle Association, and an executive steering committee. A planner from Seattle Department of Transportation that worked on this initiative provided some key insights from her experience. The plan aimed to integrate disparate modal master plans (bicycle, freight, pedestrian, and transit) and allocate downtown street space to respective modes so that properties and businesses could anticipate how the area's infrastructure and traffic patterns would develop. Ultimately, each partner contributed $10 million towards a $30 million portfolio of transit-related investments in Center City. Each partner agency had to address their own set of institutional barriers in the planning process. Each agency had its own decision-making process; SDOT could authorize transportation projects on Seattle streets without Mayoral or City Council approval, King County Metro decisions required approval from a council of elected officials, and Sound Transit decisions required approval from its board. Having different timelines and constraints slowed the agencies' ability to build consensus around a plan for Center City (Shepard, 2019). Nonetheless, the existing relationships between each of the three agencies remain strong. Each maintains willingness to return to the negotiating table, especially under high-priority issues that concern Center City; they continue to partner on numerous projects and efforts.

CONGESTION PRICING POLICY CONTEXT

Congestion pricing is a strategy that uses tolls to manage roadway or highway congestion. Cordon pricing is a specific type of congestion pricing. It is most commonly used to manage congestion on downtown streets. Internationally, cordon pricing has proven effective at managing congestion, reducing greenhouse gas emissions, and increasing transit ridership. As a result, cordon pricing is being considered in Seattle as a strategy to meet the city's congestion, emissions, and transit growth goals. Other American cities facing similar challenges today are also considering cordon pricing.

Historically, the challenge of traffic congestion has often been met with road expansions or additional roadway capacity. However, transportation practitioners today are more wary to introduce more roadway capacity because of space limitations and the potential to induce additional traffic demand. Instead, Seattle political leaders are currently considering some form of congestion pricing as an alternative transportation system management strategy. In general, forms of congestion pricing are considered road management strategies that require little additional infrastructure. Congestion pricing works by charging drivers a fee or toll to access a certain segment of roadway or a certain area in a city. By increasing the cost of driving on certain routes or in certain areas, fewer people choose to drive there, and traffic congestion and travel time reliability usually improve.

Cordon pricing is a specific form of congestion pricing. It works by charging drivers either variable or fixed tolls or charges to drive into a certain zone or cordon in a city. In international cities where it has been implemented, the cordon typically encompasses the central business district, where road space is most limited and subject to the most severe congestion. Seattle's downtown traffic issues are particularly being exacerbated by an unprecedented convergence of road closures and growing congestion. Therefore, cordon pricing is the congestion pricing variant best suited to manage existing roadway capacity on streets in Center City Seattle.

The charge to drive into a cordon zone can vary by time of day or level or congestion. This provides the flexibility to charging drivers according to traffic demand. At peak travel times when demand is highest, raising the cordon charge can smooth traffic demand so that drivers either avoid the most congestion region or choose to travel when it is less congested.

Cordon pricing can be implemented as an application or extension of existing electronic tolling systems, such as the system that operates on several Washington State highways today called Good to Go. Good to Go, like E-Z Pass in the Eastern United States and FasTrak in California, works by either scanning a mounted Good to Go pass or license plate when it passes through a tolling gantry. The system is all-electronic, so vehicles do not slow down as they pass through the gantry. The toll can be set to vary throughout the day or for different types of vehicles, and can be collected in one or both crossing directions (Washington State Department of Transportation, 2019).

Advocates for downtown congestion pricing in its various forms often cite international examples of its efficacy. Cordon pricing has already been implemented in London, Stockholm, and Milan. Each city implemented it between 2003 and 2007, and continue to operate some form of it today. Each city observed around 20 percent in vehicle traffic reductions and greenhouse gas emissions within their cordons after the implementation of cordon pricing. Transit ridership where available also increased. During implementation in these European cities, a serious effort to implement congestion pricing in New York City also took place, led by then-mayor Michael Bloomberg. In 2007, the city included congestion pricing as a transportation initiative in a citywide plan. However, in 2008 the State Assembly failed to vote to authorize Bloomberg's congestion pricing proposal, even though it had passed in the New York City Council (Confessore, 2008). It did not rise to the forefront of the policy agenda in the city for another ten years.

Because several American cities are grappling with similar congestion challenges as Seattle, policymakers around the country have opened or re-opened dialogue around the potential use of congestion or cordon pricing in their cities. No North American city has yet implemented cordon pricing in a zone of their city. New York City will likely be the first American city to do so. In 2017, the New York governor crafted a new congestion pricing proposal and instituted a task force to study the issue. Two years of debate, mixed opinions, and growing public acceptance in New York City followed. In March 2019 the New York State legislature passed a 2019 state budget that included congestion pricing and approved New York City to advance congestion pricing for the first time (Hu, 2019).

Los Angeles Metro’s board of directors and the San Francisco County Transportation Authority have also each authorized new feasibility studies for congestion pricing in early 2019.

In 2017, the Seattle City Council authorized a study on road pricing in downtown Seattle. In 2018, Mayor Jenny Durkan allocated $1 million within the citywide budget and a portion of a $2.5 million Bloomberg Philanthropies grant to be used to study congestion pricing with the potential to implement by 2021 (Downtown Seattle Association, 2018; Robertson, 2018).

Congestion or cordon pricing will be a political issue in Seattle because it must be approved by a public vote before its implementation. Furthermore, various interest groups in the region have competing goals.

Under RCW 36.73.065, Washington state law allows cities to form Transportation Benefit Districts, which can levy transportation tolls on city and county roads. These tolls cannot be imposed by a district until a majority of voters in the district approve it in a general or special election. The City of Seattle has already been a Transportation Benefit District since the Seattle City Council passed Ordinance 12339 in 2010. Therefore, Seattle would first need to hold a public vote before implementing cordon pricing on its city and county roads (Washington State Legislature, 2019).

Transportation network companies (TNCs) that operate in the greater Seattle region such as Uber and Lyft have already their position on cordon pricing clear. In October 2018, Uber stated that they would lobby for congestion pricing in Seattle, because they "believe that one of the most effective ways to manage vehicle congestion is through road pricing" and that they plan to "bring attention to the benefits of comprehensive congestion pricing from both an emissions and traffic reduction standpoint." Lyft also publicly commented that they would support congestion pricing in Seattle (Lloyd, 2018). Both companies are advocating for congestion pricing as an alternative to a surcharge or tax that is levied only on ridesourcing trips, which has also been under consideration in Seattle since Fall 2018 (Beekman, 2019).

A member of Lyft's transportation policy team shared the company's policy position and perspective. Lyft supports universal congestion pricing in Seattle and in other metropolitan areas when it is designed under certain principles. First, to meaningfully address congestion issues any policy needs to both target all vehicles and incentivize a shift to higher occupancy and shared rides – these are goals that a ridesource-only surcharge would not only fail to meet but potentially hinder. TNCs indeed contribute to traffic congestion, as do all vehicles on the road. However, congestion has been an issue far longer than their existence and TNCs still make up only a fraction of total vehicle trips; thus, charging only TNCs as a congestion relief strategy would likely be ineffective. Furthermore, Lyft supports a fee structure that incentivizes shared rides and low-carbon vehicles. This could be achieved by reducing fees on high occupancy vehicles and electric vehicles that enter the cordon. Finally, the revenue collected from congestion pricing should be reinvested in the transportation network to help provide alternative options and improve infrastructure, rather than used to fill budget shortfalls elsewhere in the city. By improving the transportation system using the revenue generated from drivers in Center City, the quality of all mobility services and modes (including those that Lyft offers, such as ridesourcing, bikesharing, and scootering, and exposing nearby transit options) will improve; when this happens, people's perception of viable means of transportation expand, which can lead to the multimodal future that Seattle envisions (Schrimmer, 2019). Many of Lyft's goals seem to be complementary with many of those held by the regional and local transportation agencies in Greater Seattle.

Although the most recent and visible discussions around congestion pricing have centered around the City of Seattle, the Seattle Department of Transportation, and the Seattle City Council, congestion pricing has previously provided fodder for regional discourse. In 2015, King County convened a Bridges and Roads Task Force to discuss an anticipated funding gap of $250 million to $400 million a year towards maintaining transportation infrastructure in the county. Furthermore, King County Metro's 2019-2020 budget lists financial sustainability as a major challenge, citing that "Metro's existing revenue structure is heavily reliant on sales tax, which is a highly volatile revenue source" and that "Metro's current revenue streams are insufficient to provide the system and services outlined in Metro Connects, Metro's long-term vision" (Metro Transit, 2018). One of the key recommendations made by the Task Force was that the county should further study funding alternatives, naming road pricing and congestion pricing as potential strategies (King County, 2016). The Greater Seattle region, like many others in the United States, is currently anticipating funding gaps that will stand between them and more a connected, sustainable, and equitable transportation system. Furthermore, state and local governments' reliance on federal transportation dollars is threatened by diminishing gas tax revenue and Highway Trust Fund insolvency.

The problems that congestion, emissions, equity, and transportation funding pose in the region have elevated cordon pricing as a potential policy solution. The current political landscape in Seattle, with its new mayor and her interest in cordon pricing, produces a window of opportunity to use evidence-based evaluations of cordon pricing to advance the policy-making process.

PROBLEM STATEMENT

To meaningfully assess cordon pricing for policymakers in Seattle, we must document the potential impacts of cordon pricing. Choosing the criteria by which we evaluate impacts is informed by the local context of transportation needs. Based on the scan of transportation, social, and climate issues, the four dimensions most relevant to the region's goals are: congestion, revenue, equity and multimodality, and greenhouse gas emissions.

Transportation is an inherently regional issue. First, transportation system impacts on travel behavior reach across jurisdictions. Most travel into Center City is generated by people who live outside Seattle. Imposing a fee to enter Center City may reduce vehicle miles travelled (VMT) within its bounds and within Seattle, but it could merely shift trips outside of the city and thus increase VMT or emissions elsewhere. Or, it could be effective in incentivizing Seattle residents to take alternate modes within Center City, but without viable drive alone alternatives for those who reside outside Seattle the fee could be less effective than is expected. Second, how cordon pricing revenue should be allocated both towards different programs and within different geographies belongs within a regional scope of discussion because of the first point. The drivers that pay the cordon price will hail from across and outside of the region; meanwhile, those who choose to take transit may produce positive externalities throughout the region via reduced congestion and emissions. Moreover, it is possible that much of the revenue collected will come from the highest-income or lowest-need travelers, or those who have cars and can afford to pay to access Center City by car. Given the complex mix of strategic goals and funding challenges that the transportation system faces, jurisdictions and agencies beyond Seattle and iSODT stand to gain or lose from Center City cordon pricing.

The unique convergence of problems, policy solutions, and political interest in cordon pricing motivates the exploration of how it can be a regional strategy that advances multiple agencies' goals and meets multiple types of peoples' needs simultaneously.

RESEARCH QUESTION

This thesis seeks to understand two major policy questions about cordon pricing in Center City Seattle. First, will cordon pricing be effective at managing congestion and emissions, and should Seattle implement it? Second, how will different investment portfolios using cordon pricing revenue produce different outcomes for the regional transportation system, and what are the implications for various regional partners?

THESIS SUMMARY

In order to present the results of these questions in terms meaningful to policymakers across the region, I synthesize metrics from strategic and long-range plans published by the City of Seattle, King County Metro, and Sound Transit. Next, statistical models provide data-driven tools for projecting the impacts of cordon pricing in terms of these key metrics. Finally, my findings are used to discuss cordon pricing from both a transportation system management perspective and a policy perspective.

Chapter 2 presents a literature review on the impacts that shared mobility and ridesourcing have had on the transportation system, how travel behavior models can be adapted to incorporate these are other new modes, and on the impacts, outcomes, and best practices of existing and emerging congestion pricing initiatives. Chapter 3 presents statistical models for estimating ridesourcing level of service variables to supplya travel mode choice model. Chapter 4 presents mode choice models for work and non-work trip types in the Greater Seattle region that incorporate drive alone, shared ride, ridesource, transit, walk, and bike modes. Chapter 5 applies these mode choice models to three settings in the Greater Seattle region – current conditions, cordon pricing with Seattle-centric investment, and cordon pricing with regional transit investment – to assess congestion, emissions, equity, and multimodality outcomes. Chapter 6 synthesizes analytical findings with local and regional strategic goals and funding needs to motivate a strategy for regional coordination around cordon pricing, and raise existing questions around policy, programming, and implementation that require future research.

Chapter 2: Literature Review

This chapter scans the states of research and practice of both congestion pricing and ridesourcing. Modern cities today face numerous challenges, ranging from longstanding ones such as traffic congestion and road safety to new ones like the introduction of unseen shared mobility services such as ridesourcing. As a result, to meaningfully assess congestion pricing within the context of a modern transportation system, we must consider the impacts that ridesourcing may have on congestion and how ridesourcing trips may uniquely respond to congestion pricing.

Numerous disciplines have contributed their perspectives on how to evaluate and assess the impacts associated with ridesourcing services and congestion pricing, including economics, transportation engineering, urban planning, geography, and public policy. Although the research methods used across these disciplines can vary, they are often applied with similar motivations or research questions. This literature review will reach across disciplines and methods in order to synthesize early findings on the most common and relevant research questions pertaining to both topics, including: understanding the demographics and geography of its users; the interactions ridesourcing has on travelers' mode choice, the impacts that the adoption of ridesourcing has had on urban traffic congestion and what policy interventions experts have recommended to mitigate such impacts; the use and effectiveness of congestion pricing as a tool for managing urban congestion; and the feasibility and guiding principles for modern congestion pricing implementation.

CONGESTION PRICING TERMINOLOGY

High occupancy toll (HOT) lanes and cordon or area pricing are two emerging forms of road pricing in the United States. HOT lanes operate as carpool lanes that single occupancy vehicles can enter for a fee. Revenue from HOT lanes is typically used to fund the highway expansion associated with creating that lane. HOT lanes are typically implemented to improve and manage traffic flow. On the other hand, cordon pricing and area pricing charge a fee when a vehicle enters or exists a defined area or zone, or when vehicles circulate within a zone, respectively. These forms of pricing can currently be found in the downtowns of a few European and Asian cities, such as London, Stockholm, Singapore, and Milan.

Other terms commonly used when discussing road pricing include: dynamic or variable pricing, in which rates or tolls vary with demand; distance-based charging, in which vehicles are charged based on distance traveled; congestion point charging, in which vehicles pay a charge when crossing key points; and managed lanes, which are similar to HOT lanes in that those who pay a toll in addition to those in high-occupancy vehicles can access it (TransForm, 2019).

This thesis will use the term congestion pricing to refer to the general concept of road pricing on downtown roads (as opposed to on freeway or highway lanes), and cordon pricing to refer to the zone-based implementation of congestion pricing.

CONGESTION PRICING IN THE U.S. AND ABROAD

European cities have been first to implement congestion pricing, including London, Stockholm, Malta, Rome, and Milan. Singapore also uses congestion pricing; they take a more comprehensive approach of pricing highways and major arterials with twenty-eight control points across the city.

London implemented congestion pricing in central London in 2003. The charge is eight pounds during daytime travel hours on weekdays. The city has observed a 15 percent reduction in traffic and a 30 percent reduction in delays, with most former car users switching the public transportation.

Stockholm implemented cordon pricing in its central business district in 2006. They experienced a 20 to 25 percent reduction in traffic volumes on the most congested roads, and a 14 percent reduction in exhaust emissions. The initial 2006 trial won the support of many voters and in 2007 they moved to institute cordon pricing permanently (FHWA, 2008).

Milan instituted cordon pricing in 2007 to reduce vehicle emissions. In 2012 Milan began prioritizing traffic reduction as well. First, Milan implemented fees that scale according how the emissions factor of the vehicle, then in 2012 replaced that with a more comprehensive charge. Milan observed that traffic reduction between 2015 and 2011 was 29.2 percent and that the scheme reduced particulate matter emissions by 15% (Croci & Ravazzi, 2015).

Although these European examples mostly predate the emergence of TNCs and ridesourcing, recent increases in traffic congestion and declining transit ridership in North America have generated the political impetus to re-investigate the feasibility of congestion pricing. As transportation practitioners and policymakers anticipate the introduction of automated vehicles and the potential increase in VMT associated with that transition, congestion pricing is being proposed as the cornerstone of a policy package that addresses a multitude of emerging urban issues (Hirsh, Higashi, Mason, and Catts, 2019).

In the United States, congestion pricing discussions have advanced most in New York City (NYC). New York Governor Cuomo formed the Fix NYC Advisory Panel in late 2017 to develop recommendations to address severe traffic congestion in Manhattan's central business district (CBD) and identify subway revenue sources. The panel recommended a phased approach, ultimately implementing congestion pricing in the city;

furthermore, cordon pricing as a solution would uniquely be able to charge ridesourcing vehicles. They prioritized zone or cordon pricing over managed lanes and increased vehicle registration fees due to implementation ease and inequitable impacts, respectively. In the proposed first phase, the city would install zone or cordon pricing infrastructure so that trips that cross into the CBD would be charged a fee during certain times of the day or week. In the second phase, all for-hire vehicles (both taxis and TNCs) would be charged a Congestion Surcharge in the CBD, with the potential for variable rates based on time and day of week, and lower rates for pooled rides. All revenue would be used for transit improvements. In the third phase, zone or cordon pricing would be imposed on all vehicles that enter the CBD, including both trucks and passenger vehicles (HNTB, 2018). Ultimately the proposed plan would charge cars $11.52 during peak hours, trucks $25.34, and taxis and ridesource vehicles $2 to $5, generating $1.5 billion yearly.

The response to the proposed congestion charge in NYC has been mixed. Policy scholars are generally in favor of congestion pricing because it is efficient, charging drivers for the negative externalities that their behavior generates (Short, 2018). TNCs themselves have also begun to embrace the policy, likely in recognition that congestion pricing will serve as a fairer policy that is enforced on all vehicles. Uber's Head of Transportation Policy and Research formally shared the company's stance on congestion pricing in 2017, stating that "the cost of driving ultimately needs to reflect its cost to our cities" (Morris, 2017). In March 2019, the New York State legislature passed a state budget that would allow New York City to implement congestion pricing on all vehicles by 2021. 80 percent of revenue would be spent on subways and buses and 10 percent respectively to Long Island Rail Road and the Metro-North Railroad (McKinley & Wang, 2019).

Transportation professionals have also been prominent voices in the congestion pricing debate in NYC. Bruce Schaller, an expert on for-hire vehicle-related issues, has authored numerous reports on congestion and ridesourcing in NYC. His reports evidence that TNCs have contributed to congestion in the city and have suggested congestion charging as a tool for mitigating those impacts on multiple occasions. However, although he does state congestion pricing and TNC fees would be effective congestion mitigation strategies, he anticipates they will be politically infeasible. Based on his analysis, a fee on TNCS must be as high as $50 per hour in Midtown Manhattan to disincentivize cruising on streets without riders and to reduce the associated VMT. In anticipation of potential political barriers to aggressive pricing policies, Schaller instead suggests strongly limiting the parking supply in NYC; it would be more politically feasible to adopt than congestion pricing, while still likely reducing the number of people who choose to drive into the CBD. Another solution proposed is limiting or banning low-occupancy vehicles from certain streets at designated times of the day in the CBD (Schaller, 2018). Although a divergent congestion pricing proposal in NYC is now in development, the principles and recommendations Schaller put forth may transfer well to other American cities with similar challenges.

Despite the aforementioned political barriers, other cities in the U.S. and Canada have also considered implementing some form of congestion pricing. Vancouver conducted a study on "decongestion charging" in 2018, motivated by the region's traffic congestion. It discusses the need for new forms of coordination and policy to manage emerging transportation technologies like electrification, automation, and sharing. The study found that regional congestion point charges would reduce congestion by 20 to 25 percent and raise $1 to $1.5 billion per year, while multi-zone distance-based charges would reduce congestion by 20 to 25% and raise $1 to $1.6 billion per year. The study also named four principles to guide the design of a mobility pricing policy: congestion, fairness, supporting investment, and other matters like economic benefit, privacy, and regional growth. The report recommends that "a decongestion charge should be coordinated with all the other ways we pay for mobility in Metro Vancouver - including new and emerging mobility services - to achieve regional mobility goals." On funding, the report recommends that "the design of a decongestion charge should seek alignment of charges with access to transit. This can be supported by targeted transit improvements" (Mobility Pricing Independent Commission, 2018).

In 2010, the San Francisco County Transportation Authority (SFCTA) conducted a feasibility study on congestion pricing in San Francisco concerning transportation, economic, environmental, social, and financial conditions. It also discussed how transit and active modes could be improved by using the revenues generated through pricing. The report found that congestion pricing would be technically feasible and would advance the city's goals relating to transportation system management, greenhouse gas emissions reductions, and sustainable economic growth. A cordon fee in Northeast San Francisco was projected to decrease vehicle trips to and from that area by more than 15 percent. The report also proposed that a program would fund faster and more frequent transit services and coordinate to deliver additional transit services prior to the introduction of the congestion charge. The report found that given a $3 cordon charge, annual revenue would be around $450 million, though discount programs for low-income and otherwise disadvantaged travelers would reduce revenue by about $90 million. The report also named the importance of regional agreements that would be necessary to implement cordon pricing in San Francisco, including with the Metropolitan Transportation Commission/Bay Area Toll Authority, San Francisco Municipal Transportation Agency, and California Highway Patrol (SFCTA, 2010). In February 2019, SFCTA authorized a new $500,000 study to re-examine congestion pricing in downtown San Francisco (SFCTA, 2019).

Transit agency Los Angeles Metro announced that they would recommend pursuing congestion pricing in January 2019. In March 2019, the Metro board voted unanimously to move forward on congestion pricing and ridesourcing fee feasibility studies. In Los Angeles, this initiative is motivated by both present recurring congestion and anticipated 2028 Olympics congestion (CBS Los Angeles, 2019). Separate from LA Metro, the Southern California Association of Governments (SCAG) conducted the Mobility Go Zone and Pricing Feasibility Study, exploring how the use of decongestion fees could have impacts on VMT and VHT. SCAG chose the Westside area in the Cities of Los Angeles and Santa Monica as a proof-of-concept area because of its high congestion and high jobs-to-housing ratio. The report found that a cordon zone would reduce VMT within its boundaries by 22 percent during the AM peak and 21 percent during the PM peak. The report also found that driving mode choice would decrease by 19 percent during peak periods, while transit and active mode shares would increase by 9 and 7 percent respectively. The report suggests future research on the impacts on low-income households with vehicles as well the potential for a low-income or carpool discount. The report also suggests additional analysis to assess the impacts to traffic congestion if TNCs are subject to differential pricing or an hourly rate instead of a flat fee (SCAG, 2019).

CONGESTION PRICING POLICY STRATEGIES

In addition to the previously reviewed studies, which examine the feasibility of congestion pricing within specific urban areas, some literature provides broader implementation and planning recommendations and principles. This work contains of mix of studies with both predate and follow the emergence of TNCs and the popularization other new mobility services.

In 2008, the Federal Highway Administration published a series of primers on congestion pricing, included road pricing, parking pricing, and mileage-based user fees. These primers synthesized lessons learned from numerous U.S. and international cases to produce recommendations and best practices. The primer series had several goals. The first was to motivate policymakers to consider congestion pricing as part of a bundle of complementary strategies that would be acceptable to a range of stakeholders; policymakers could find allies among decisionmakers and local leaders and engage businesses to build broad-based support for a congestion pricing program. The second was to link congestion pricing to regional goals and objectives, with ongoing monitoring and evaluation. The third was to find interagency collaboration opportunities and partnerships that clearly identify regional roles and responsibilities, sometimes with the help of political leadership. The fourth was to analyze regional traffic, economic, and social impacts of congestion pricing to inform the planning process. The fifth and final recommendation was to establish a supportive policy framework for implementing regional pricing programs and establishing conditions for revenue use (FHWA, 2008).

One of the primers FHWA produced in this series focused on congestion pricing and its effect on public transportation. An international scan found that the effect of congestion pricing on public transportation depends on the type of pricing strategy that is implemented. HOT lanes do not generate a shift to public transportation even though some revenues from the lanes are occasionally dedicated to public transportation. FHWA noted that in London, a core part of the congestion charge strategy had been to implement the charge alongside enhanced public transportation services: 300 new buses were introduced several months before London implemented the congestion charge. FHWA noted that in London, ridership into the zone increased by up to 38 percent, due both to the congestion charge and transit service improvements. One institutional solution that made this coordination possible was that Transport for London was granted final authority for both transit and road projects in London, which made it easier to integrate transit investment with the congestion charge. FHWA found that enhanced public transportation made zone-based pricing successful in Europe, which suggests that contemporary efforts in the United States should also include transit investment a core strategy within a congestion pricing proposal (FHWA, 2009).

FHWA also published a primer on the income-based equity impacts of congestion pricing, raising equity issues associated with road pricing. For instance, most forms of transportation finance, such as fuel taxes, sale taxes, and tolls have been found to be regressive relative to income. Furthermore, congestion pricing could disproportionately burden low-income workers by making it difficult to reach their jobs, especially if adequate transit is lacking. Finally, there may be barriers for households that do not have access to lines of credit or bank accounts. They found that high-income individuals are more likely to incur congestion charges, while low-income individuals benefit the most from pricing schemes when revenues are used for public transportation. The primer put forth several strategies for addressing equity concerns. One consideration is how congestion pricing revenue will be used - whether revenue is used for financing highway improvements or transit service shifts the distribution of costs and benefits. Another consideration is toll exemptions or toll rebates for low-income or otherwise disadvantaged drivers. The primer also found that this was an issue that mattered specifically in Seattle, based on a survey conducted in 2007: hypothetical tolling was much more likely to garner public approval when its revenue would be used to fund transit and bicycling investments, demonstrating that Seattleites value equity over avoiding or lowering tolls. Ultimately, the primer suggested either toll-financed transit improvements and low-income exemptions or rebates would best compensate for otherwise disproportionate burdens on low-income travelers (FHWA, 2008).

More recent work has discussed strategies for designing a road pricing that benefits all road users, especially vulnerable communities. Non-profit TransForm published an equity toolkit in 2019 designed to guide decision-makers at each step of the planning process of a road pricing proposal. TransForm's toolkit recommends five steps. The first step is to identify the populations that would require attention from the equity perspective, the type of road pricing under consideration, and the geographic reach of the study area. Some vulnerable communities that they suggest include low-income communities, minority populations, seniors, persons with disabilities, immigrants and refugees, and local small businesses. The second step is to define equity outcome and performance indicators. These indicators could fall under either process equity, which could be measured by full public participation, or outcome equity, which could be measured by affordability, access to opportunity, and community health. They also recommend a comparative analysis of impacts to vulnerable communities and the general population under "no toll" and "with toll" scenarios. The third step is to determine the benefits and burdens of proposed alternatives. They suggest that technical models can be useful for projecting likely reactions to changes in the transportation system, but planners need to know the limits of the models and their interpretations. The fourth step is to choose strategies to advance transportation equity. They recommend generating a portfolio of strategies within a broader equity program, and assessing each for their potential impacts. The fifth and final step concerns post-implementation, and it is to provide accountable feedback and evaluation. They recommend monitoring and evaluating important impacts and translating findings to decision-makers and affected communities. Ultimately, TransForm stresses that the process they outline is iterative and dynamic, because congestion pricing itself needs to be considered a dynamic process; downtown congestion pricing will need to be evaluated and adjusted periodically, which will require continuous evaluation and community engagement (TransForm, 2019).

RIDESOURCING TERMINOLOGY

The introduction of ridesourcing services to the urban mobility landscape in the early 2010s has inspired a growing body of academic and applied research. Though the services have been referred to by many names, including “real-time ridesharing,” “parataxis,” “ridematching,” “on-demand rides,” “app-based rides,” “ridehailing,” and “ridesourcing,” (Rayle et al., 2014) this thesis refers to the service as ridesourcing because the SAE Shared and Digital Mobility Committee considers this the standard term (SAE International, 2018). It will also refer to the providers of the service as Transportation Network Companies (TNCs). Though ridesourcing services are privately provided, its adoption has certain impacts on public issues including congestion, transportation sector emissions, and social equity; therefore, understanding the demographics, geography, operational impacts, and impacts of policy interventions (such as congestion pricing) around ridesourcing are fundamental to public agencies’ missions.

RIDESOURCING AND TRAVEL BEHAVIOR

Household travel surveys are typically collected every several years, so many traditional sources of travel behavior information have been too infrequently collected to supply complete insight into who uses ridesourcing services, when and where they travel, and for what trip purposes. For instance, the last two years in which the National Household Travel Survey was collected were 2009 and 2017 (FHWA, 2017). In the eight years between those two waves of the survey, the mobility landscape evolved significantly. The

2017 wave was the first opportunity to survey participants on their ridesourcing travel behavior, a full six years after Uber launched in San Francisco (Huet, 2014). Furthermore, TNCs themselves have been reluctant to public share data about their operations and riders in order to protect what they consider to be proprietary business information (Marshall, 2018). As a result, transportation researchers have mostly turned to administering their own surveys to understand early ridesourcing adopters and how its use interacts with transit ridership and vehicle ownership, while more subsequent studies have been able to utilize household travel surveys and other larger data sources.

One of the earliest surveys was conducted in San Francisco in 2014. It found that respondents who made ridesourcing trips were younger and had more education than the average population. The study compared TNC trips with taxi trips; it found that ridesourcing served a similar market as taxis because many surveyed said they would otherwise use a taxi for the same trip. However, the survey also noted that there was not complete overlap of the two markets, as some respondents indicated that they chose ridesourcing to save time compared to a similar transit trip (Rayle et al., 2016). Findings from this survey foretold what would become an important research question: whether or when TNCs competed with or complemented public transit service.

The Pew Research Center incorporated questions about ridesourcing use in the December 2015 wave of its American Trends Panel, which is nationally representative of all U.S. households. At the time, they found that 15% of American adults had experience using ridesourcing applications, while one-third had never even heard of the services. Among those who did use it, more than half were infrequent users, using it less than once a month. They also found that young adults, college graduates, high-income individuals, and urbanites were most likely to have used ridesourcing. The survey found that frequent ridesourcing users are less likely to own a car and more likely to use other modes such as walking, biking, transit, bike-sharing, and car-sharing (Smith, 2016). This survey motivated later examinations of ridesource and its interactions with transit service, multimodal behavior, and vehicle ownership. In 2018, Pew provided updates to their first survey. They found that the percent of people surveyed who used ridesourcing increased from 15 percent in 2015 to 36 percent in 2018. They also found that 18 to 29-year-olds, college graduates, and people with incomes about $75,000 a year were still more likely than other demographic groups to use ridesourcing. They also found that the share of people who used ridesourcing frequently had not changed, which could suggest that although more people were aware of ridesourcing or have tried it, it had not dramatically altered habitual travel choices (Jiang, 2019).

The Transit Cooperative Research Program (TCRP) sponsored a survey on shared mobility and its impacts in 2015. They covered seven American metropolitans, including the Seattle-Tacoma-Bellevue metropolitan area. They examined ridesourcing services, bike-sharing, and car-sharing. They surveyed shared mobility users, local transportation officials and practitioners, compared representative travel times by various shared modes, and discussed practical opportunities such as paratransit provision and other models for public-private partnership. They found that shared mobility users were more likely to also use transit, own fewer vehicles, and spend less on transportation. The survey found that ridesourcing trips are more commonly taken for recreation and social purposes, late at night, and in situations where travelers will be drinking alcohol. They also found evidence that shared modes both competed with and complemented transit services, though ridesource trips were most popular at times when transit is typically unavailable. However, the most commonly reported substituted mode for ridesource trips was driving alone or with another person, not transit. Because of these findings, the study recommended that public entities seek opportunities to partner with private shared mobility providers

(National Academics of Sciences, Engineering, and Medicine, 2016). The evidence in this report highlights the importance of distinguishing between different trip purposes when considering the implications of policies, fees, and regulations on ridesource travel behavior.

FiveThirtyEight also examined ridesource user demographics and travel behavior in 2015 in one of a series of analyses using New York City Taxi & Limousine Commission data. They found that TNC and taxi passengers are highly concentrated in wealthier areas of New York City, which contrasts with Rayle's finding in San Francisco in which there was not a significant gap between ridesource users' salaries that those of the general population. This could be because in New York City middle-class residents are actually more likely than wealthy residents to own vehicles due to the abundance of transit service in wealthy NYC neighborhoods. They hypothesized that areas where ridesourcing is popular coincides with areas that transit is popular because the two services complement each other, while in areas where transit service is poor travelers are accustomed to using personal vehicles (Silver & Fischer-Baum, 2015). This analysis suggests how the context of a city's demographics and infrastructure can influence the relationships between ridesourcing and travel behavior.

Researchers at the University of California, Davis Institute of Transportation Studies also conducted a multi-city survey. They surveyed participants in seven U.S. cities, including Seattle, in both 2014 and 2016. They found that parking availability, or a lack thereof, was an influential factor in the decision to choose ridehailing over driving. They also found that situations involving alcohol motivated the use of ridesourcing over personal vehicle use. Their observations about the demographics of ridesourcing users also concurred with previous and simultaneous efforts, with evidence that those aged 18 to 29, with college education, affluent, and urban residents were more likely to use ridesourcing.

They also found ridesourcing users to have higher personal vehicle ownership rates than people who only use transit. The ultimate direction of the impact ridesourcing use has on vehicle ownership is likely complicated and context-specific: for some users, ridesourcing is a substitute for vehicle ownership, while for others it is a facet of a generally automobile-oriented lifestyle. The survey found evidence that ridesourcing competes with bus and light rail, but complements commuter rail. Finally, the survey found that ridesourcing was perceived to be mostly distinct from other modes including walking, biking, and transit, which led them to hypothesize that ridesourcing use will likely contribute to growth in VMT (Clewlow & Gouri Shankar, 2017)

A Toronto 2016 travel survey found evidence that wealthier, younger people are more likely to use ridesourcing. The study also found evidence to suggest that the introduction of ridesourcing has likely reduced driving while intoxicated (Young & Farber, 2019). In addition to examining demographics most associated with ridesourcing use, the study presented a use case for ridesourcing that would be socially beneficial, which suggests that policies around ridesourcing will need to balance the benefits and drawbacks of the mode; for instance, how can a policy or fee discourage the use of ridesourcing as a substitute for transit and active modes, while not disincentivizing ridesourcing as a substitute for late-night drunk driving?

More recent studies of ridesourcing behavior have begun to use individual-level statistical methods to examine ridesourcing adoption and frequency. Circella et al. (2016) surveyed shared mobility service users in California, include car-sharing, ridesourcing and bike-sharing modes. They used a binary logit adoption model and found that millennials (ages 25 to 34 in 2015), the highly educated, residents of urban locations with greater land-use mix, and those with technology-embracing, pro-environment, and variety-seeking attitudes are more likely to use ridesourcing. They used an ordered probit model to show that individuals without vehicles, long-distance (by plane) travelers, residents of high land-use mix and activity-dense areas, and users of smartphone apps for travel information are likely to have higher frequencies of ridesourcing use. Finally, respondents reported that ridesourcing reduced their use of personal vehicles and that ridesourcing did reduce their use of transit and travel by active modes.

Lavieri and Bhat (2018) used a web-based survey in the Dallas-Fort Worth region and applied a generalized heterogenous data model that uses psychological constructs as latent factors. They found that non-Hispanic whites are less likely to use pooled ridesourcing due to a heightened sensitivity to privacy, whereas elderly and low-income travelers are less likely to use pooled ridesourcing due to lack of technology awareness. These findings are useful for supporting other works that demonstrate that travelers have varied reasons for using ridesourcing. A policy framework must consider how different travelers will respond to services changes in order to accurately assess its impact.

Dias et al. (2017) used a bivariate ordered probit model to understand both the frequency of use of ridesourcing and car-sharing services. The study was conducted using Puget Sound Regional Council (PSRC) household travel survey data from 2014 and 2015. They found that users of both services tend to be young, highly-educated, higher-income, employed, and from higher-density areas.

The recent release of the 2017 National Household Travel Survey beget a number of studies. This survey, due to its national scope and consistent administration, has inspired researchers to examine trends that emerged between 2009 (the second-most previous survey wave) and 2017. One analysis found that since 2009, for-hire ride services (including both TNCs and taxis) have experienced an increase of riders due to a disproportionate growth in use from upper-middle class households and lower-middle class households (Securing America’s Future Energy, 2018). This could imply that although early findings typically suggested that wealthier individuals were more likely to use ridesourcing, the service has transitioned to a broader customer base in recent years. King, Salon, & Conway (2018) compared data from the 2009 and 2017 NHTS waves and found that in 2017, transit users were more likely to also be ridesourcing users. They interpreted this to mean that ridesourcing and transit were mostly complementary. However, they noted that vehicle ownership could be a crucial mediating factor, as those who forgo car ownership might generally increase transit ridership, while those who do not would use ridesource as a substitute for private vehicle use instead. This has been noted in previous studies, which highlight the complicated nature of the relationships between ridesourcing and other travel behavior decisions such as mode choice and vehicle ownership.

The research area on ridehailing, demographics, and travel behavior has evolved since the earliest studies from around 2014. As ridesourcing questions have been incorporated into larger household travel surveys, researchers have been able to leverage more powerful statistical methods to uncover associations between user demographics, trip characteristics, and the adoption and frequency of ridesource use. This body of work has raised important policy debates, supported guiding principles, and beget future research efforts, the most common of which concern: recommendations for public entities for partnering meaningfully with private mobility providers and assessing and addressing the impact that ridesourcing has on vehicle miles traveled (often through road pricing and regulations).

RIDESOURCING AND SERVICE EQUITY

Another research area regards the fairness of TNC service quality. Because early research found that ridesource users are more likely to be younger, wealthier, better education, and more urban, evaluating the equity of ridesource services from a variety of dimensions has become an important pursuit.

Smart et al. (2015) conducted an experiment in low-income Los Angeles neighborhoods, comparing the wait time and trip cost of ridesourcing and traditional taxis. This study was funded by Uber and performed by researchers at the University of California, Los Angeles and the BOTEC Analysis Corporation. The experiment instructed participants to call for a taxi and an Uber ride at the same time to compare the wait times and total trip cost of various trips. They found that Uber rides consistently were less expensive and had shorter wait times for pick-up than taxis in the low-income neighborhoods where the experiment was conducted. However, the study did not compare ridesource level-of-service in low-income neighborhoods with level-of-service in other neighborhoods in the region, so no conclusions could drawn about whether ridesource service is equitably provided throughout greater Los Angeles.

Hughes & MacKenzie (2016) estimated wait times for UberX vehicles throughout Uber's service area within the greater Seattle region using the Uber developer application programming interface (API) in 2015. They estimated a regression model of wait time and found that high population, high employment density, and midday timing are associated with shorter wait times, while higher average income in an originating census tract was associated with longer wait times. The study defined access to TNC services based on the expected wait time, and found that access was not restricted to wealthier parts of the city. They also found that the percentage of minority residents in an analysis zone was not associated with wait times, which led the researchers to conclude that there was no evidence of racial discrimination. However, the expected wait time given by the API is not necessarily a true wait time, which means it is still possible that drivers discriminate against certain types of riders.

Thebault-Spieker, Terveen, & Hecht (2017) used a similar methodology in late 2014. This study also used observations from the Uber wait time API in order to model expected wait times, but in Cook County, Illinois in the Chicago area. They too found that population density and average wait time were inversely related. However, unlike the study undertaken in Seattle, they observed that as neighboring tracts' average income increased or the percentage of white residents increased, wait times decreased. The study authors concluded that there was evidence of structural racial and ethnic biases in the sharing economy, and pointed out that the issue was intersectional, as low-income communities also tend to contain a higher percentage of ethnic minority residents.

Wang and Mu (2018) used a similar methodology in Atlanta. They used the Uber API to collected estimated wait times for both UberX and UberBLACK service models. Their unit of analysis was the neighborhood level. Using spatial regression, they found that population density, road network density, lower vehicle ownership rates, and higher numbers of public transport stops were all associated with lower UberX wait times, while higher mean travel times to work are linked to increases in average UberX wait times. They did not find evidence that median house value or minority rate were statistically associated with UberX wait times. The value of comparing these three similar studies is limited because they were conducted in different parts of the U.S.; unobserved factors unique to each region could be driving the differing conclusions. Nevertheless, the juxtaposition of these three studies motivates further research on whether there are systemic biases that lead to differing levels of ridesource service for different types of riders.

Ge, Knittel, MacKenzie, & Zoepf (2016) further examined this issue using a randomized experiment in Boston, MA and Seattle, WA. Similar to the one deployed in Los Angeles, the experiment used participants of varying racial backgrounds and each used two names to request ridesource rides, one a "white-sounding" name and the other a "distinctively black" name. In this study, there was evidence of racial discrimination by wait time, with black riders experiencing 29% to 35% longer wait times for a ride, primarily due to a longer time spent waiting to be accepted by a nearby driver to provide a ride. They also found that black riders were more than twice as likely to experience cancelled trips than white riders, particularly black male riders. This study evidenced that discrimination and inequity through ridesourcing services could occur through a variety of mechanisms and cannot necessarily be captured by aggregate or zonal level of service.

Finally, Brown (2018) also sought to understand what geographic features are associated with ridesource access and search for evidence of racial or gender discrimination through ridesource and taxi services. The study was focused on Los Angeles County. The author found strong associations between ridesource use and low household vehicle ownership, suggesting that ridesourcing can provide automobility to those that may otherwise lack access to vehicles. The author found that black riders were more likely to experience cancelled taxi trips and longer wait times than white riders, but not for ridesourcing trips. However, there may still be barriers to ridesource access that exist for numerous other populations: un-banked or under-banked populations and those who do not own smartphones, who are thus unable to access and pay for ridesource services; riders (particularly women) who fear harassment from drivers or other passengers in a shared ride; seniors who are less comfortable using newer internet-based services; and individuals with physical disabilities, who often face longer waiting times due to the lesser availability of disability-accessible ridesource vehicles.

RIDESOURCING, VEHICLE MILES TRAVELED, AND CONGESTION

Another key research question is whether ridesourcing increases vehicle miles traveled (VMT) or otherwise contributes to traffic congestion. This question has links to that of ridesourcing competition with transit services; because mass transit is more space-efficient than private vehicles, losing transit riders to ridesourcing is one of several potential ways in which ridesourcing could increase traffic congestion. Additional time and fuel spent due to traffic congestion has negative economic impacts. In 2015 the Texas A&M Transportation Institute estimated in their Urban Mobility Scorecard that travel delays due to congestion wasted 3 billion additional gallons of fuel and 7 billion additional hours spent in traffic, with a national economic cost of $160 billion (Schrank, Eisele, Lomax, & Bak, 2015). Therefore, understanding causes of and strategies to reduce traffic congestion is a worthy goal, and uncovering potential impacts from ridesourcing is critical to that goal.

Bialik, Flowers, Fischer-Baum, and Mehta (2015) of FiveThirtyEight produced one of the first data-driven analyses of the issue. They compared taxi service with TNC service in NYC, discovering a geographic concentration of TNC trips in NYC's CBD. Using data from 93 million Uber and taxi trips taken between April 2014 and September 2014, they noted that both Uber's and taxis' Manhattan pickups were concentrated in Downtown Manhattan, which has both the best level of subway service and the most traffic congestion. A subsequent analysis by Fischer-Baum and Bialik (2015) also found evidence that Uber had added more congestion to Manhattan's CBD than had other for-hire vehicles such as taxis. Although between 2014 and 2015 Uber's market share had eroded the taxi market share in the CBD, the net number of for-hire vehicle passenger pickups (taxis and ridesource vehicles combined) had remained nearly constant.

Meanwhile, a controversial 2015 New York City Council initiative proposed capping the number of vehicles Uber could operate in the city, primarily motivated by concerns that ridesourcing was increasing congestion in Manhattan. Ultimately, the mayor announced the city would first conduct a study evaluating the traffic impacts of ridesourcing in the city before regulatory action. The For-Hire Vehicle Transportation study was published in early 2016. It used the city's travel demand model (called the Best Practice Model) projections, New York City Taxi and Limousine Commission data, and e-dispatch trip records. The study concluded that the observed reduction of vehicle speeds in the Manhattan CBD were primarily due to increased freight movement, construction activity, and population growth. It posited that ridesourcing had minor contributions to congestion in the CBD, but that the future growth of the ridesourcing industry could contribute to future increases in congestion. The study noted that regulatory intervention of ridesourcing would be eventually necessary if it continued to take over the taxi mode share, because the yield from taxi surcharges and accessibility fees that fund transit would decrease (City of New York, 2016).

A 2017 analysis examined trends in trips, passengers, and mileage from TNCs and other for-hire vehicles in NYC between 2013 and 2016. It used electronic trip logs, for-hire vehicle (FHV) trip volumes, transit ridership, and total personal travel by all modes. They found between 2013 and 2016 FHVs added 52 million additional passengers, mostly due to the growth of TNCs. It also found that TNC growth increased VMT by 600 million miles from 2013 and 2016, even after the introduction of pooled or shared ride options. The report noted that it matters who is riding TNCs: if ridesourcing attracts ridership from taxi riders into pooled rides, or private vehicle drivers, then it could reduce overall travel in the city. However, if it attracts transit riders, it will increase travel. This is consistent with themes that other authors have discussed. It also matters where trips are added: the study found that TNC trip growth added a significant number of trips in already-congested neighborhoods, like the Manhattan CBD (Schaller, 2017).

In August 2018, NYC's city council voted to become the first major American city to cap the number of for-hire vehicle licenses granted for a year. The mayor cited increased congestion due to TNCs for the action, although other political factors such as increasing suicide rates within the yellow cab industry also contributed. TNCs and their supporters have argued that under a cap, demand will outpace driver supply, leading to higher prices and longer wait times. Uber advocated instead for congestion pricing, which would toll all drivers in Manhattan. An legislation also stipulated that the city re-study the congestion impact of ridesourcing, so the continuing debate in NYC could inform how other American cities regulate the ridesource industry (Fitzsimmons, 2018).

Researchers have studied ridesourcing's impact on congestion in metropolitan areas outside of New York City as well. Li, Hong, and Zhang (2016) used a panel data approach to estimate the impact that Uber entry in a metropolitan market had on urban congestion. The dependent variable was Texas A&M Transportation Institute's Travel Time Index. They also estimated a similar regression using the Commuter Stress Index as a dependent variable, which is an index that measures peak hour traffic congestion. These indices have been calculated several times between 1982 and 2014 for 101 urban areas in the U.S. The researchers found that Uber availability is associated with lower traffic congestion. The study posited that some explanations for this finding could include: a net reduction in vehicles on the road; a reduction of vehicles particularly during peak travel times; and a higher vehicle capacity utilization from shared rides. This is one of the few studies that presents evidence that congestion has decreased since the advent of ridesourcing and that studies multiple American metropolitans within the same framework.

Alexander and González (2015) used call detail records from cell phone traces to derive trip origin-destinations in the Boston metropolitan in 2015. They estimated the mode shares of drive alone or taxi, carpool, and non-driving modes, which inferred ridesourcing mode share. They used traffic assignment to estimate the travel times within the transportation network. They used the network model to assess the impact of ridesourcing during peak weekday evening hours. They concluded that it mattered who used ridesourcing: if people who would otherwise drive used ridesourcing, particularly pooled ridesourcing, then there would be a reduction in total vehicles on the road. On the other hand, if more non-drivers adopted ridesourcing, then the number of vehicles on the road would increase.

A recent study led by SFCTA used a unique data source, created by combining data mined by Northwestern researchers from the Uber and Lyft APIs and data from INRIX. The SFCTA estimated that daily VMT in San Francisco had increased by 630,000 miles between 2010 and 2016, with TNCs accounting for 40 percent of the daytime increase and 60 percent of the evening increase. The analysis also found that TNCs most contributed to increased congestion in the densest parts of the city. This study firmly concluded that TNCs increased congestion in San Francisco. This study has had a direct influence on TNC policy in San Francisco: in August 2018 the city began taxing Uber and Lyft 3.25 percent of their net revenue from single-occupancy rides and 1.5 percent of their net revenue from shared rides (CBS SF BayArea, 2018).

Schaller (2018) assessed the impact of ridesourcing on congestion in 20 urban areas, including Seattle. Schaller found a positive correlation between cities with high transit commute shares and TNC use. The study concluded that TNCs compete with public transportation, walking, and biking. Tt estimated that TNCs add 5.7 billion miles of driving the 9 largest metropolitan areas, including Seattle. It was estimated that TNCs added 94 million additional miles traveled in 2017 in Seattle. Therefore, the study concluded that increasing TNC trip volumes contributed to the observed increase in congestion nationwide.

There is a growing body of literature on whether or not TNCs contribute to congestion, and if so, when and where they add the most VMT. There is general consensus that it matters who is using ridesourcing services, as the impact of a single occupancy vehicle driver switching to ridesourcing is different than that of a transit rider switching to ridesourcing.

Shared Mobility Policy Strategies

Ridesourcing has had measurable impacts on numerous facets of traveler behavior. This has implications for existing infrastructure systems, transit demand, traffic congestion, and the needs and expectations of the modern traveler. Researchers and practitioners have taken steps to develop best practices and guiding principles for public agencies to integrate existing systems with new mobility services.

The American Planning Association published the guidebook *Planning for Shared Mobility*. Cohen and Shaheen (2016) scan the interactions between shared mobility services and urban planning goals and outputs, including: travel behavior, land use, urban design, housing, economic development, environmental stewardship, and climate action. The guidebook scans policy levers that have impacts on shared mobility's growth and adoption. Ot notes that "at the municipal level, the most common ways local and regional planning and policies influence shared mobility are through the allocation of public rights-of-ways (e.g., parking, curb space), developer and zoning regulations, insurance and for-hire vehicle ordinances (e.g., licensing), and taxation." The authors acknowledge that taxation has the most critical impact on ridehailing out of all shared mobility modes, and by increasing service costs policymaker could adversely affect adoption of shared mobility services. The authors acknowledge that "tax issues affecting on-demand ride services, such as Lyft and Uber, are more complex. Whether drivers or on-demand ride services should pay sales taxes remains an unresolved issue." This underscores the continued need for policy analysts to weigh various trade-offs when deciding how to regulate TNCs or charge all vehicles to use roads – for instance, taxing them could reduce their accessibility by increasing fares or wait times for pickup, yet without any intervention the negative externalities they produce from additional VMT could go unmitigated.

FHWA prepared a white paper on the integration of shared mobility from the regional planning or MPO level. Kevin, James, Glynn, and Lyons (2018) interviewed 13 metropolitan areas, including Seattle, to synthesize current practices and future recommendations in shared mobility. Some of the key challenges spanned safety, equity, congestion, pollution, land use impacts, and identifying sustainable revenue models. The authors argue that MPOs are well-positioned to lead their regions in shared mobility planning activities because they can facilitate collaborative regional decision-making. For instance, one of the roles that an MPO takes in the regional planning process include coordinating planning interventions, such as: regional policy; regulation coordination; partnerships with shared mobility providers; communication forums; and development of incentives. MPOs can coordinate cities' regulation of the use of the public right-of-way, preventing a patchwork of local regulations. Failure to do so could unnecessarily increase private mobility service providers' compliance costs or produce unintended distortive economic effects. The white paper recommended MPOs integrate shared mobility into their travel demand modeling activities.

The adoption of Shared Mobility Principles for Livable Cities (2017) illustrated the willingness for global collaboration. Their mission statement is that "Sustainable, inclusive, prosperous, and resilient cities depend on transportation that facilitates the safe, efficient, and pollution-free flow of people and goods, while also providing affordable, healthy, and integrated mobility for all people." These principles were produced by a working group of international NGOs. There are 10 principles in total, including: prioritizing the movement of people over vehicles, open data, and seamless connectivity between modes. One principle calls for fair user fees across all modes, suggesting that "every vehicle and mode should pay their fair share for road use, congestion, pollution, and use of curb space." These principles align with themes raised in the U.S.-centric documents previously discussed, such as motivating multi-sector coordination, efficient regulation and taxation, and setting multi-modal objectives. Numerous governments, not-for-profits, and private mobility service providers (including Uber and Lyft) have joined as signatories, representing countries and cities all over the world.

Another example of shared mobility guiding principles comes from the local level. The Seattle Department of Transportation developed a New Mobility Playbook in order to provide guidelines to new mobility service providers on using the public right-of-way, and provide recommendations for their operations so that they align with greater transportation system goals. The New Mobility Playbook outlined strategies and initiatives for integrating ridehailing into a comprehensive Seattle transportation system. For instance, barriers experienced by unbanked riders could be mitigated by: educating residents about existing and new payment options, partnering with web-based third-party payment methods that accept cash, or adding operational requirements for app-enabled mobility services for alternative payment methods. To ensure new mobility services are Americans with Disabilities Act (ADA) accessible across the region, the playbook suggested setting maximum wait times by geography and time of day and educating TNC drivers about the varying needs the mobility-impaired. The playbook suggested: implementing guaranteed ride home partnerships with TNCs; subsidizing shared mobility services for transit passengers; and testing the use of transit only lanes by non-transit high occupancy vehicles like shared ridesource trips. The playbook also recommended collaborating with local and statewide partners to develop umbrella regulatory frameworks for new mobility services in recognition that partnership with other agencies will aid in aligning regulatory and operational goals. The playbook suggested variable fee mechanisms for TNCs could increase vehicle occupancy and manage congested corridors.

As researchers and practitioners aggregate best practices, some themes emerge. An immediate step that local agencies have taken is to regulate TNCs' use of public right-of-way, such as the use of curb space for passenger drop-off and pickup, and parking pricing. However, cities and regions are also considering taxation and fees, which motivates careful consideration of how these policies might shape the demand for shared mobility services, such as ridesourcing. Another recommendation is to consider congestion pricing to manage traffic that might be produced by all private vehicles on the road, included ridesourcing vehicles.

RIDESOURCING FEES AND TAXES

There is a growing interest in taxing new mobility services. Additionally, cities around the world are considering implementing congestion pricing. These discussions have begun to dovetail, as consensus builds around the contribution TNCs have to traffic congestion.

In 2018, the Eno Center for Transportation performed a scan of existing fees and taxes on TNC trips. At the time of publication, seven major cities and 12 states had implemented some type of fee or tax on TNC trips. Seattle charges a flat fee on rides that originate in the city. Kim and Puentes (2018) caution that policymakers should consider the impacts that taxes will have on transportation behavior. They identify four major motivators for implementing fees: offsetting the negative effects of urban congestion; funding infrastructure and public transit investment; producing fairness in regulation of TNCs are compared to traditional taxi services; and creating funding streams for regulatory costs such as improved wheel-chair accessibility services in for-hire vehicles. The authors suggest that an alternative to targeted TNC fees could be: charging fees on all SOVs like a congestion charge; providing exemptions or lower prices for shared rides; or some combination of policy levers that might be less distortive. These suggestions motivate research that simultaneously assesses the behavioral implications of various policies and practical considerations like the potential to use revenue to fund transit and accessibility-related initiatives.

The debate around ridesource charges and taxes has evolved rapidly. Charges on ridesourcing in the U.S. include excise taxes, surcharges, and sales taxes. Lawmakers weighing taxation of TNCs did not initially anticipate that ridesourcing would be a significant source of tax revenue (Quinton, 2015). Instead, regulatory issues focused on permitting and public safety-related regulations, such as background checks, fingerprinting, and insurance coverage. This is changing as more lawmakers implement fees. Meanwhile, TNCs have spoken against the implementation of fees and charges on ridesourcing around the country. They argue a surcharge on ridesourcing vehicles would unfairly target consumers and reduce the quality of service. However, sales taxes have already typically been extended to include services, and ridesourcing is considered a service. Therefore, precedence exists for ridesource taxes. (Farmer, 2018).

Chapter 3: Predicting Ridesource Level-of-Service Variables

FUSING METHODS AND DATA SOURCES

This thesis estimates the impacts congestion pricing will have on mode choice, vehicle miles traveled (VMT), and other transportation system outcomes. Chapter 4 uses two multinomial logit mode choice models to achieve this: one each for work and non-work trips. However, both models require information about trips that are typically not collected in household travel surveys. For instance, if a person in the survey is observed to take a single occupancy vehicle trip, the level-of-service that the traveler would have experienced for a carpooled trip, transit trip, walking or bicycling trip, or ridesource trip is usually not collected, but is a necessary model input to estimate a conditional or multinomial logit model. Therefore, it is necessary to use alternate data sources for these unobserved trips where possible, or estimate what level-of-service variables would have been for unobserved modes. Because estimating those variables for ridesourcing is particularly difficult due to the lack of TNC-provided data and gaps in existing travel surveys, this chapter estimates ridesource-specific level-of-service variables. The two variables of particular interest are ridesource pick-up wait time and trip fare.

As discussed in Chapter 2, there is a small body of literature that is related to ridesource trip wait times. One of these studies even focuses on the Seattle-Tacoma region. These use spatial regression techniques. The strength of these techniques is their interpretability when attempting to uncover geographic or demographic trends at a zonal level. The method can account for spatial correlations, such as when a zone surrounded by other zones with low wait times is more likely to also have lower wait times. The method can also uncover statistical associations, such as how neighborhoods with higher population densities or higher average incomes tend to experience lower wait times. Such results are useful for high-level views of the geography of ridesource service and availability, particularly for uncovering where ridesource coverage is weaker or service is relatively poor. However, the predictive power of these methods is weak because their objective is to provide an average wait time for an entire zone conditional on zone-wide characteristics, not to predict the wait time of a particular trip based on trip-specific characteristics like trip distance or time of day. In other words, the goal of regression is to explain trends, not to predict. Therefore, the use of regression methods is less-than-ideal for the application at hand, where an accurate point estimate of a level of service variable in a multinomial logit model is critical. To overcome the limitations of statistical methods like spatial regression for the objective of prediction, this approach uses machine learning algorithms.

DATA

I collected region-specific data on ridesource wait times and trip fares in order to build a robust predictive model. The collection process was undertaken in late November 2018 and early December 2018. It used the publicly-accessible Uber and Lyft APIs because these are the two most popular TNCs that operate in the greater Seattle region.

Between November 18th, 2018 and December 8th, 2018, a Python script was deployed to collect 27,788 observations from the Uber Ride Request API and the Lyft Ride Request API. Both APIs require authentication to access, but anybody can request such a token or ID. Both APIs provide estimated wait times and fares for different services given trip origin and destination coordinates. Therefore, the trip cost and wait time of an UberPool or Lyft Line (the respective shared ride offerings) are distinct from the classic private ridesource product (Uber Technologies, 2019; Lyft, 2018). The script only collected UberX and Lyft estimates (the private option) because they serve as a midpoint between the pooled trips and SUV or luxury offers which are typically costlier and less available. Because the mode choice analysis is limited to ridesourcing as an overall mode rather than distinguishing between shared and private ridesource trips, it is reasonable to use UberX and Lyft estimates, because these are the most popular service offerings of each company. Both APIs provide a range of trip fares, specifying a minimum and maximum value. These fare estimates were averaged to produce a final estimated trip fare. Furthermore, the Lyft API produced an estimated time of arrival (ETA) in seconds, whereas the Uber API produced a more general trip duration estimate. Upon comparing the magnitudes of these values, it was concluded that the Uber API trip duration estimate was that of the entire trip time, including wait time and travel. As a result, only the Lyft wait time was used to estimate an expected trip wait time for each observation.

In order to maximize coverage of the Seattle region, the collection process randomized the origin and destination traffic analysis zone (TAZ) for each observation. These were randomly sampled from a list of TAZs in which a ridesourcing trip was observed in the PSRC 2017 household travel survey. Some descriptive summaries of the collected dataset are presented below to illustrate its breadth.

Variable	Count	%
Day of Week		
Monday	3308	11.9
Tuesday	6005	21.6
Wednesday	4414	15.9
Thursday	2780	10.0
Friday	4234	15.2
Saturday	4467	16.1
Sunday	2580	9.3
Time of Day		
12 AM – 3 AM	3930	14.1
3 AM – 6 AM	3146	11.3
6 AM – 9 AM	3053	11.0
9 AM – 12 PM	3229	11.6
12 PM – 3 PM	3452	12.4
3 PM – 6 PM	3417	12.2
6 PM – 9 PM	3734	13.4
9 PM – 12 AM	3827	13.8
Trip Origin TAZ		
In Seattle	18080	65.1
At Airport	92	0.3
Trip Destination TAZ		
In Seattle	13246	47.7
To Airport	77	0.3

Table 1: Trip Variables in Ridesource Level-of-Service

There is a roughly equal distribution of observations collected on each day of the week and across different times of day. More than half of all ride requests are made in TAZs that are within Seattle city limits, and nearly half of all ride requests are made for trips that end within Seattle. Continuous variables recorded in the dataset include trip distance in miles, average estimated fare, and estimated wait time.

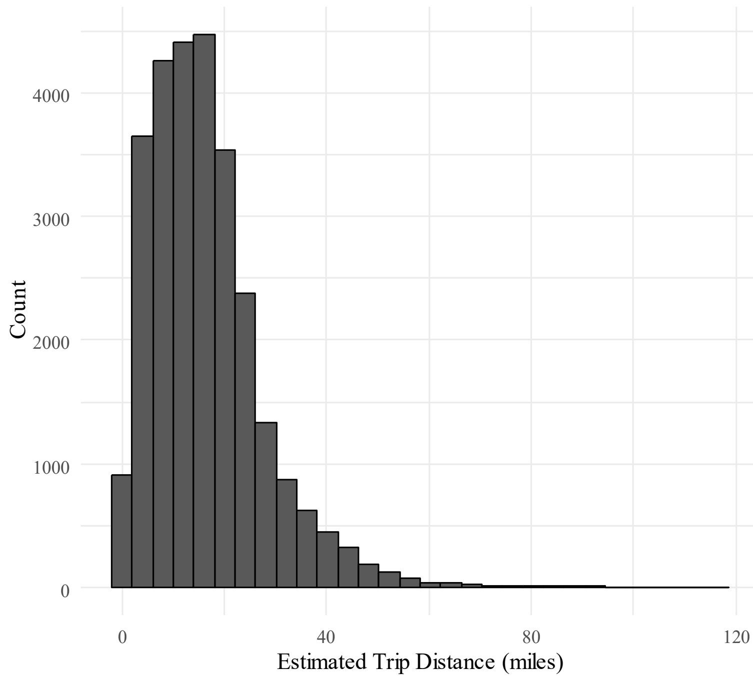

Figure 1: Observed Distribution of Ride Request Trip Distance

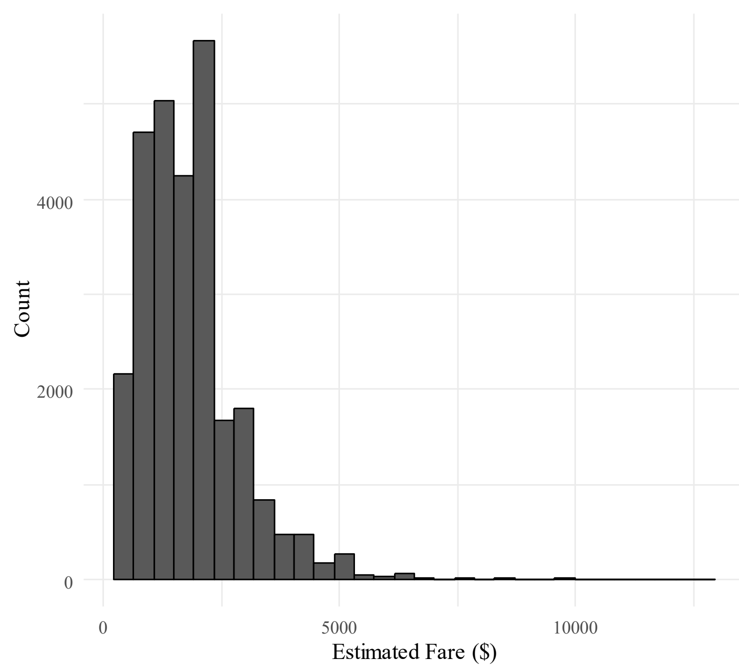

Figure 2: Observed Distribution of Ride Request Estimated Fare

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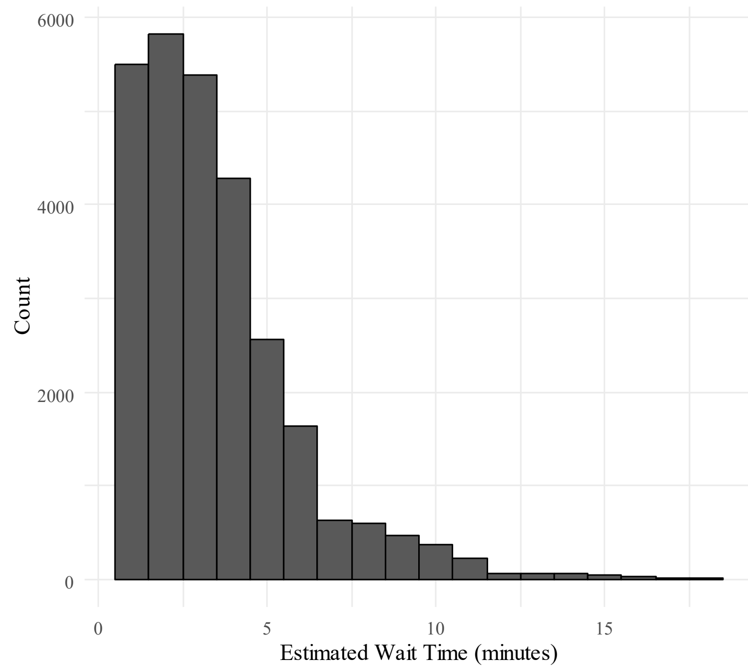

Figure 3: Observed Distribution of Ride Request Estimated Wait Time

The distributions of trip distances, estimated fares, and estimated wait times are skewed right, likely due to the data collection methodology which collects trips concentrated where ridesource trips are most frequent. Because those trips are observed in higher frequency in or near the city of Seattle, most of the sampled trips either begin, end, or are contained within the city limits and are thus shorter in length. However there are still some ride requests in excess of 80 miles or in more remote TAZs where wait times may be significantly longer than they are near downtown Seattle.

Finally, this dataset is joined with land use data provided by PSRC. From the land use data set, the household density (households per square foot), employment density (total employees per square foot) and university student density (total university students per square foot) can be derived for each ride request observation based on the origin and destination TAZs.

There are a number of limitations resulting from the design of the data collection process. First, only a few observations exist in the TAZs that house the Seattle-Tacoma International Airport. This could be improved in future studies by sampling more frequently from those TAZs as ridesource trips from the airport may exhibit patterns in wait times and surge pricing that differ from those in other parts of the study area. Second, the methodology only collects ride request data from the 1,242 TAZs where a ridesource trip is observed to begin in the PSRC household travel survey and the 1,721 TAZs where a ridesource trip is observed to terminate in the survey. The data set would offer more coverage if it sampled from all 3,600 TAZs in the PSRC region. Third, because origin and destination TAZs for ride requests were generated independently, many trips observed are much longer than the average ridesource trips observed in the PSRC household travel survey. Because the objective of this analysis is to predict ridesource trips' wait times and costs, and many of such trips are relatively shorter in length compared to personal automobile trips, it may be more useful to bias data collection towards trips of lengths typical of those observed in the travel survey. Fourth, the data was collected in Fall 2018, but it will be used to infer level-of-service variables for hypothetical trips in Spring 2017. There could be differences in level-of-service due to seasonality or change in service popularity as a result of the temporal mismatch between the ride request dataset and the PSRC household travel survey. Nonetheless, the dataset collected is rich and contains general insights about how various spatial, temporal, and geographic characteristics of a trip relate to ridesource level-of-service.

METHODS

Choosing a data analysis method or approach depends on the data available and the analysis objective. After choosing a broader approach, statistical or algorithmic, a specific model form must be selected. This can be done empirically by comparing multiple models using some measure of model performance or accuracy. Finally, once a specific model framework has been selected, building a final model that can be used for the prediction of level-of-service variables requires specifying predictor variables and other model parameters to optimize model performance.

Modeling Approach

Given the goal of predicting the outcomes of two continuous variables, ridesource wait time and fare, there are two distinct strategies: statistical models and algorithmic models.

The statistical model is the traditional approach. One of the most common statistical models is ordinary least squares regression; others include forms of penalized regression, Bayesian regression, and semiparametric models. These models are applicable when the goal is to identify a relevant and interpretable population parameter. For instance, the estimated parameters of an ordinary least squares approach enable interpretation of the isolated effect or association of various regressors on a response variable.

The second approach is algorithmic, or machine learning-based. Instead of seeking to identify statistical parameters, the algorithmic approach allows for more flexibility. For instance, while ordinary least squares regression assumes that the response variable can be modeled by a linear combination of certain regressors, an algorithmic approach does not typically isolate the effect of a single variable. Some models of this family are random forests, bagged and boosted tree ensembles, support vector machines, and neural networks. The second approach is algorithmic, or machine learning-based. Instead of seeking to identify statistical parameters, the algorithmic approach allows for more flexibility. For instance, while ordinary least squares regression assumes that the response variable can be

modeled by a linear combination of certain regressors, an algorithmic approach does not typically isolate the effect of a single variable. Some models of this family are random forests, bagged and boosted tree ensembles, support vector machines, and neural networks. These models are strong in pattern recognition, which necessitates a large quantity of data.

Ultimately, statistical models are appropriate if the goal is to: isolate effects of a small number of variables; the analyst wants to understand the uncertainty of a prediction or the effect of a predictor; additivity of multiple predictors is significant; the sample size is small to moderate; and the model needs to be interpretable. On the other hand, machine learning is appropriate if: prediction over interpretability is the goal; it is not as important to estimate the uncertainty of a prediction; the sample size is huge; and there is no need to isolate the effect of a specific variable such as a treatment effect (Harrell, 2018).

Given the respective strengths of the two approaches, the algorithmic or machine learning approach is more appropriate for the application of predicting ridesource level-of-service. Uncertainty in prediction does matter, but because a point estimate will be used as an input for a subsequent model, being able to estimate the variance of the prediction is not critical. Furthermore, because the aim is not to understand how different types of neighborhoods might experience different ridesource service quality or availability, isolating the impacts of specific predictors is not critical to the overall goal of prediction. Therefore, there is a theoretical basis for selecting a machine learning approach.

Preliminary Model Selection

Performing an empirical comparison of both statistical and algorithmic models can build support for the theoretical basis of using machine learning for ridesource level-of-service prediction.

Multiple models can be compared at a high level using resampling methods. This can be done using R, which has a package *caret* that can compare 237 different models. First, several models for comparison are selected, including a mix of statistical models and machine learning models. The statistical models chosen are linear regression (ordinary least squares) and lasso generalized linear models (regularized). The machine learning models are k-nearest neighbors, radial support vector machines, random forest, and gradient boosted machines.

A brief overview of each type of model under consideration illustrates the distinctions between different modeling approaches and individual models. Ordinary least squares models are estimated by minimizing the sum of squared errors. Lasso is a regularization technique applied to linear regression that modifies the objective function. Whereas in ordinary least squares the goal is to minimize the squared errors, lasso minimizes the sum of squared errors plus a penalty equal to the absolute value of the magnitude of the estimated coefficients. The result of this additional penalty is resulting coefficient estimates that are biased to be small, and have fewer nonzero estimators or predictors, resulting in a reduced model. When there is high collinearity among predictors, this approach can outperform ordinary least squares (MathWorks, 2019).

The k-nearest neighbors (KNN) algorithm is a nonparametric method, unlike regression which assumes a linear-in-parameters functional form. KNN is one of the best-known non-parametric methods because it is straightforward. In order to predict the value of a response variable, it combines continuous predictions based on the average observed values of the k observations closest to the predictor. When using multiple predictors, it interpolates, averages, or performs a local linear regression to arrive at a single point estimate of the response variable. KNN has a number of drawbacks, such as sensitivity to outliers and lower performance under high dimensionality, but it is simple and requires few assumptions (Béjar, 2012). Support Vector Machine (SVM) is a class of algorithms that minimizes error akin to traditional regression. The twist is that there is a margin of tolerance for error, so the sum of squared errors cannot exceed some margin. Because it may be infeasible to find a line whose sum of squared errors does not exceed the maximum margin, soft margins are introduced which allow some errors to exist. The advantage of SVM over linear regression is that it can deal with overfitting and nonlinearity (MathWorks, 2019). A random forest is an ensemble of bagged decision trees. A decision tree breaks down a sample into subsets based on the values of predictors (or features) to improve prediction accuracy at a given observation. Bagging trees is done by creating multiple decision trees on bootstrapped subsamples of the dataset, then averaging their predicted responses to provide a single response. The random forest algorithm selects a random subset of predictors that make up each individual tree in the ensemble. By adding such additional randomness, it prevents overfitting and can be used to identify the features with the highest importance or predictive power (Donges, 2018). Gradient boosting machines (GBM), like random forests, are ensemble models where the average of multiple models produces the ultimate prediction. Under boosting, an ensemble is constructed sequentially by intentionally selecting data points to be included in the next subsample that were previously poorly predicted. Gradient is in the name of this algorithm because it uses gradient descent to minimize the mean squared error. An advantage is its reputation for high predictive accuracy and flexible function fit, but it can be prone to overfitting due to its approach of addressing errors that may be caused by outliers (Boehmke, 2018).

The *caret* package enables the analyst to rapidly train various models. Resampling is used to evaluate the effect of model tuning hyperparameters on performance. A model hyperparameter is a configuration that is external to the model and is often specified by the analyst. To "tune" a machine learning algorithm is to seek the hyperparameters of a model that result in the best model performance (Brownlee, 2017). The hyperparameters that must be tuned are specific to a model. For instance, in a lasso regression a hyperparameter which must be tuned is the shrinkage factor, or lambda, which controls the magnitude of the penalty term that regularizes estimated regression parameters. In random forest, hyperparameters are the number of decision trees that make up the ensemble and the number of features used to split a node.

Tuning complicated models such as random forest and gradient boosting machines can become a lengthy process, requiring the estimation and evaluation of numerous iterations of a model. Selecting a 5,000-observation subset of the full 27,000-observation dataset speeds the training process of multiple models. The tradeoff between using the full dataset and training speed leans in favor of the former because this initial step aims to achieve a high-level comparison of model performance rather than maximizing the performance of a single model. There are various approaches to evaluating the performance or accuracy of a model. Repeated cross validation generates a more robust estimate of model accuracy compared to standard k-fold cross validation or using a single testing and training dataset split. The procedure of k-fold cross validation is as follows: split the dataset into k groups, and for each unique group hold it as a testing data set while the remaining groups are used to train the model. The observed evaluation metric, typically root mean square error or r-squared, is then reserved. Under k-fold cross validation each data observation is used in a test dataset once, and k evaluation metrics are observed. Under repeated cross validation the standard procedure of k-fold cross validation is repeated, but the dataset is shuffled before the dataset is split into k groups (Brownlee, 2018). This analysis uses 10-fold cross validation with 3 repeats, so 30 resamples and evaluation metrics are collected for each of the six models. The results of each model where wait time and trip fare are the predicted variables are summarized below.

	Minimum	25th Percentile	Median	Mean	75th Percentile	Maximum
OLS	0.110	0.138	0.160	0.161	0.178	0.257
Lasso	0.113	0.139	0.160	0.162	0.178	0.260
KNN	0.058	0.092	0.102	0.104	0.115	0.173
SVM (Radial)	0.091	0.129	0.146	0.146	0.156	0.217
Random Forest	0.376	0.427	0.447	0.449	0.479	0.541
Gradient Boosting	0.316	0.381	0.410	0.400	0.425	0.460

Table 2: Summary of R-squared from 30 Resamples of Wait Time Models

	Minimum	25th Percentile	Median	Mean	75th Percentile	Maximum
OLS	0.251	0.269	0.296	0.298	0.319	0.265
Lasso	0.252	0.269	0.296	0.298	0.319	0.365
KNN	0.257	0.308	0.332	0.335	0.362	0.414
SVM (Radial)	0.272	0.325	0.353	0.346	0.367	0.386
Random Forest	0.440	0.495	0.532	0.522	0.559	0.592
Gradient Boosting	0.355	0.410	0.433	0.436	0.467	0.518

Table 3: Summary of R-squared from 30 Resamples of Trip Fare Models

Across six different models to predict ride pick-up wait time, the ensemble models perform the best on an unseen test set with the highest r-squared values. Statistical, regression-based models (OLS and lasso) actually outperform the less complicated machine learning approaches (KNN and SVM). Across six different models to predict trip fares, ensemble models achieve the best predictions. In this case, KNN and SVM outperform OLS and lasso. Finally, random forest appears to outperform gradient boosting machines for both prediction of wait time and trip fare. The general conclusions drawn from this analysis are not particularly surprising: ensembled-based methods are the most flexible of all models considered. Based on the success of random forest in this initial model assessment, the final production model that will be trained on the entire data will use that modeling approach to make predictions for use in estimating level-of-service variables as inputs of the ultimate mode choice model.

This section presents theoretical justification for using machine learning, and presents the empirical evidence in support of using random forest for this specific prediction problem. Next, a final random forest model is tuned and evaluated.

Final Model

This section describes the tuning of hyperparameters of two random forest models, one for ridesource wait time and one for estimated fare. Three hyperparameters are tuned. The first is the depth of the trees in the forest, or leaf size (LS): the number of observations per leaf tend to impact whether a single regression tree overfits or underfits data. A "shallow" tree is one which does not achieve high training accuracy because it is a weaker model. Smaller minimum leaf sizes result in deeper trees. The second hyperparameter is the number of predictors to sample at each node (PTS). This parameter determines how many predictors are randomly sampled from the full set of predictors when introducing a new split in a decision tree. The "random" part of the random forest is that one of these randomly selected predictors will be selected as the best predictor to make a split in the tree. The third and final hyperparameter to tune is the number of regression trees in the forest (NT). Typically, random forests containing many trees are more accurate because ensembles that have more trees are more accurate.

Tuning three hyperparameters can be framed as a constrained optimization function. The method seeks to find the combination of these three hyperparameters that maximizes the random forest model performance, which can be quantified by a number of metrics. This analysis uses a variation of the out-of-bag error, which is the mean squared error for predictions made on observations not included in the model training data. In the case of the random forest, because there is an ensemble of trees, each of which uses different training and testing values, the analysis uses the scalar, cumulative out-of-bag error. This is the error of predicting a point using all of the trees which were not trained using that point (MathWorks, 2019).

Bayesian optimization is an optimization method that is commonly used to tune machine learning model hyperparameters. It is most appropriate for optimization problems where the objective function is continuous, but computationally expensive to evaluate. This is true in the case of hyperparameter tuning where each evaluation of the f function requires re-estimating an entire random forest model. The approach also applies when the objective function is a "black box" or has no known special structure like concavity or linearity, and we cannot observe first- or second- order derivatives which could be levered in methods like gradient descent or Newton's method. Again, this is true in the case of optimizing the performance of a random forest model with respect to its hyperparameters. In addition to specifying an objective function, in this case evaluated as the cumulative out-of-bag error for a given random forest model, we must choose an acquisition function. This function is used to project what the new value of the objective function would be at a new point based on a current posterior distribution of f based on previous iterations of the optimization process. The most common acquisition function is called expected improvement, which is an algorithm that identifies the point with the largest expected improvement based on the expectation of the posterior distribution (Frazier, 2018).

There are numerous software packages which have already implemented Bayesian optimization routines. This analysis uses a MATLAB version, and defines bounds on the hyperparameters in order to contain the solution to the Bayesian optimization problem at hand. The minimum leaf size can be between 1 and 60, to balance the tradeoff between over- and under-fitting. The maximum number of parameters to sample is one fewer than the total number of input parameters, which is a logical bound. Finally, number of trees in the ensemble can be between 1 and 600 for tractability. This optimization routine is used twice, once where the objective function is the cumulative out-of-bag error on predicted wait time, and once where the objective function is the cumulative out-of-bag error on predicted trip fare. The resulting optimal hyperparameters of these two separate optimization routines are summarized below.

	Model	
	Wait Time	Trip Fare
Minimum Leaf Size	13	1
Parameters to Sample	18	18
Number of Trees	596	520

Table 4: Tuned Hyperparameters for Random Forest Models

The above hyperparameters are next used to build full random forest models for pick-up wait time and trip fare.

MODEL FINDINGS

There are a few metrics that can be used to summarize a random forest model. The section presents the distribution of r-squared values achieved on test data using the same method of separating training and testing data when selecting an initial model: 3 repeats of 10-fold cross validation. This metric was chosen for consistency with the earlier section, but it should be noted that it was the mean-squared error, not the the r-squared value that was used to optimize the hyperparameters. Other metrics that are commonly used to summarize a machine learning model include the mean absolute error, the mean squared error, and the root mean squared error.

	Minimum	25^{th} Percentile	Median	Mean	75^{th} Percentile	Maximum
Wait Time	0.4011	0.4150	0.4198	0.4192	0.4247	0.4297
Trip Fare	0.9540	0.9573	0.9393	0.9597	0.9624	0.9665

Table 5: Summary of R-squared from 3 Repeated 10-fold Cross Validations of Final Level-of-Service Random Forest Models

The wait time model results are comparable to those of the preliminary models, while the trip fare model performs better. However, it is not possible to directly compare the results of these models with the previous ones because these were built using the full sample size whereas preliminary models used for model down-selection were built using only 5,000 randomly sampled observations. Nevertheless, these models still clearly achieve better prediction of unseen data than purely statistical or regression-based models, which would have likely produced r-squared values around 0.20.

It is not possible to isolate the individual effect of various predictors used in a random forest model. However, there are methods to quantify the relative importance of predictors in a random forest. The out-of-bag predictor importance estimates by permutation serve as one method of measuring the influence of predictor variables in predicting the response. The process to estimate the predictor importance values uses permutation of actual observations in the training data. After randomly permuting observations of a specific predictor variable, the out-of-bag model errors before and after permutation are compared. For all of these changes in observed prediction errors, the out-of-bag predictor importance is the mean of all errors divided by the standard deviation of all errors (MathWorks, 2019).

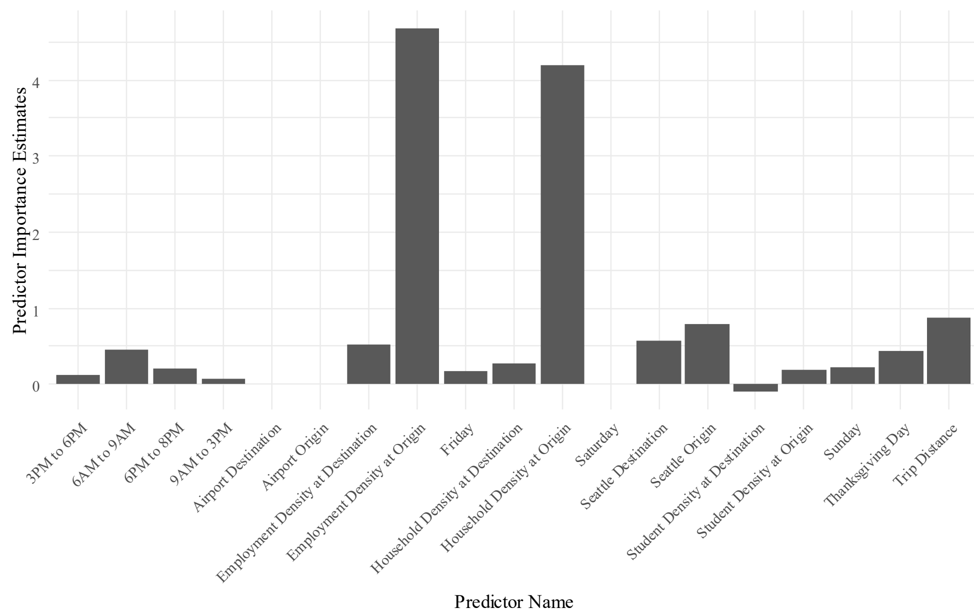

Figure 4: Estimated Predictor Importance for Wait Time Prediction

As Figure 4 evidences, the two most important predictors of wait time are the employment density and household density at the origin TAZ. The time of day and trips being in Seattle city limits are also relatively influential predictors of wait time. This is a very similar result to earlier findings which used spatial regression to estimate zonal-level characteristics' individual effects on ridesource pick-up wait time.

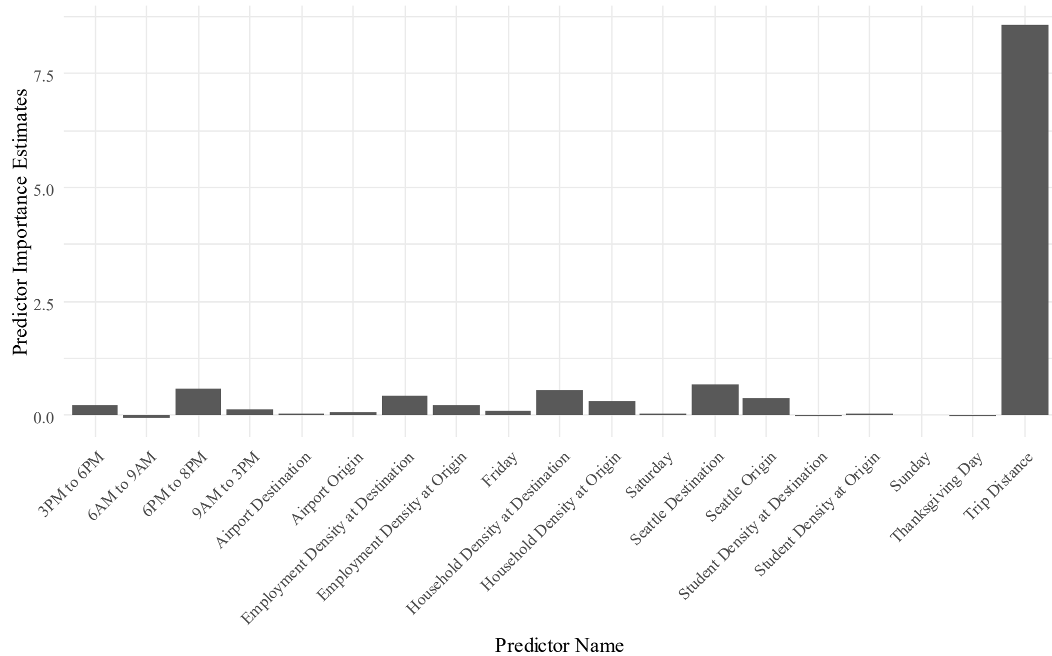

Figure 5: Estimated Predictor Importance for Trip Fare Prediction

As Figure 5 evidences, the single most important predictor of trip fare is the trip distance. This is not surprising as both services use a fare structure with a base fare and a fare based on the time and distance of the trip. The next four most important predictors of trip fare are employment density at the destination, household density at the destination, and trips with Seattle destinations, and trips that are between 6PM and 8PM.

Chapter 4: Modern Mode Choice Models for Greater Seattle

TRAVEL BEHAVIOR MODELS AND RIDESOURCING

Most of the literature on ridesourcing and its impact on travel behavior employs survey methods. Such approaches present interpretable and succinct findings. For instance, examining what mode various travelers would have taken had they not used ridesourcing sheds light on when transit and new mobility compete and complement one another. Similarly, asking travelers if they would have taken a trip at all had ridesourcing not been available can provide suggestive evidence on whether ridesourcing has increased travel demand, especially vehicle miles traveled (VMT). These methods are useful because they illuminate general trends and associations, which can motivate subsequent research questions that aim to concretize the complex relationships between travel choices.

Mode choice models or regional travel demand models that integrate ridesourcing as a distinct mode from taxis or private automobile travel are an emerging research opportunity. Research in this area only first emerged around 2017 for several reasons. First, shared mobility and related technologies are evolving rapidly, which is challenging for traditional, long-range travel demand modeling paradigms to capture. Metropolitan planning organizations (MPOs) are required per federal regulations to develop long-range transportation plans that project demand for transportation services over 20 years (FHWA & FTA, 2007). To perform the technical analyses that underpin these plans, MPOs typically conduct periodic household travel surveys and use them to maintain a travel demand model. Given that these plans are typically updated every four years (and at least every four years), and household travel surveys are conducted sometimes even less frequently, it is no surprise that cities and regions have been slow to incorporate shared mobility modes into the formal planning process. Second, despite the attention ridesourcing receives in the press and in urban planning discourse for its potential congestion impacts, it still makes up only a small proportion of all mode share. For instance, in 2018 transportation scholar Don Mackenzie estimated that ridesourcing makes up roughly 4.5% of total VMT in Seattle (Gutman, 2018). Thus, even when ridesourcing is separated as a unique travel mode in travel surveys, as PSRC began doing in 2014, there are few observed instances of travelers choosing ridesourcing to support statistical inference through discrete choice models. Finally, regional governance operating models do not particularly incentivize MPOs to meaningfully incorporate ridesourcing into travel demand modeling efforts. For an MPO to elevate a capital project or investment onto an implementation-oriented, shorter-term transportation improvement program, it often must appear on an MPO's long-range plan. As a result, modeling efforts are oriented towards identifying infrastructure investments that can provide congestion relief, emissions reductions, and safety improvements. Therefore, although ridesourcing's impacts on travel behavior may have secondary impacts on congestion and equity that have regional scope, because most infrastructure-based solutions do not directly mitigate adverse impacts from ridesourcing there is not a strong motivation for an MPO to consider how their proposed investments could impact ridesource-related travel behavior. Furthermore, ridesourcing has remained a mostly urban issue, whereas MPOs' jurisdiction typically span multiple counties with large and small cities and rural areas that may not immediately benefit from any efforts spent modeling new mobility services.

Despite the data availability limitations, the transportation practice should begin incorporating shared mobility services in rigorous travel behavior models. Cities around the world, including numerous in the United States, are investigating the potential implications of both fees and taxes on TNCs as well as broader congestion pricing schemes that would target most private automobiles. The City of Seattle has indicated strong interest in congestion pricing as a strategy to mitigate congestion, and as of 2019 is conducting a study on the issue (Robertson, 2018). Any scheme implemented in Seattle will alter the cost of travel for Seattle residents, but the impacts will reach a much broader population. Any sort of congestion pricing in Seattle would likely alter regional travel behavior; depending on the pricing scheme, some potential impacts are changes in regional access to transportation, destination choice, vehicle miles travelled, and multimodal behavior. Therefore, although congestion pricing initiatives in the United States are currently primarily city-led, it is crucial that its impacts are examined from a broader, regional lens.

This chapter addresses the need for integrating ridesourcing into regional travel behavior models by estimating two discrete choice models. Trip types are separated into work-related and non-work-related and separate mode choice models are estimated for each. These serve as an step towards using travel behavior modeling methods to understand existing ridesource-related travel behavior and towards assessing the impacts of various pricing schemes on both ridesource-related and system-level travel behavior.

DATA

The aforementioned discrete choice models are data-intensive. Although household travel surveys that observe specific individual and their travel decisions are an incredibly rich data source, most alone still are not sufficient for estimating complex travel behavior models. Consider the data required to estimate a mode choice model, where the objective is to estimate a specific individual's probability of selecting a certain travel mode to make an assumed trip: in order to identify why a certain person was observed to choose a certain mode over another, the analyst must know level-of-service characteristics of all considered trips, not just the actual trip taken. Chapter 3 tackled this issue specifically with regards to unobserved ridesource level-of-service characteristics, but this section will also discuss my approach for estimating equivalent characteristics for other travel modes as well. Additionally, land use and mode choice are linked independent of travel time and travel costs (Zhang, 2007). The PSRC zonal-level land use data was mapped to individual trips in the household travel survey. Finally, the PSRC maintains traffic network models that model expected travel times from zone-to-zone for various modes at various times in the day. This data was used to estimate the level-of-service attributes for carpooling relative to single occupancy vehicle trips, which was necessary due to the prevalence of high occupancy vehicle lanes on highways in and around Seattle.

Household Travel Survey Data

The 2017 Puget Sound Regional Travel Study was conducted as part of a six-year effort with 5 survey waves planned between 2014 and 2021. One of the goals for capturing survey waves in short succession was to employ cutting edge data collection methods in order to identify and understand emerging travel behaviors and transportation issues. The study area covered the four counties under PSRC purview: King, Kitsap, Pierce, and Snohomish, which encompasses 82 cities and towns with a population over four million people. Amongst surveyed households, 80% participated in a one-day household travel diary and 20% participated in a seven-day smartphone GPS diary. The survey was administered between April and June 2017 using address-based sampling so that all households in a certain zone had equal chance of selection. The survey collected data on household, person, and vehicle information such as vehicle ownership, age, employment, education, home location, and household income. Trip data included number of travelers, trip purpose, mode, costs, and trip start and end times and locations (RSG, 2018).

The full trip diary data contains 52,492 trip observations, which was reduced to meet the scope of the analysis.

Because ridesourcing is likely not available or a reasonable mode choice in the more rural or remote areas of the region, which include regional and state parks, the analysis was limited to trips that either began or ended in zip codes where at least one ridesource trip was observed.

The data was bifurcated into two sets: work trips and non-work trips. The two are distinguished by the trip purpose field. Work trips were those with either destination trip purposes: “went to primary workplace,” “went to work-related place (e.g., meeting, second job, delivery),” “went to other work-related activity,” or those with the aforementioned origin purposes and a “return to home” destination purpose. Non-work trips were those with either destination trip purposes: “dropped off/picked up someone (e.g., son at a friend's house, spouse at bus stop),” “went grocery shopping,” “went to other shopping (e.g., mall, pet store),” “conducted personal business (e.g., bank, post office),” “went to medical appointment (e.g., doctor, dentist),” “went to restaurant to eat/get take-out,” “went to exercise (e.g., gym, walk, jog, bike ride).” “attended social event (e.g., visit with friends, family, co-workers),” “attended recreational event (e.g., movies, sporting event),” “went to religious/community/volunteer activity,” “went to a family activity (e.g., child's softball game),” “transferred to another mode of transportation (e.g., change from ferry to bus),” “other appointment/errands,” “other social/leisure,” or those with the aforementioned origin purposes and a “return to home” destination purpose.

It is important to note that separating only by work and non-work trip types in this policy analysis is a major simplification and limitation. Such a simplification could imply priority for understanding work trips over other trip types that may be just as important. Non-work trips can equally or further contribute to an individual’s quality of life. This simplification is performed to reduce the complexity of the mode choice modeling exercise, and it is recommended in subsequent studies to give deeper consideration to more distinct trip types, such as recreation, shopping, family visits, medical care, and education.

The analysis also limits trips to those taken using modes that could be classified as personal auto (drive alone), personal auto (shared), walk, bicycle, transit, or ridesourcing. This left out certain modes such as rental car, carshare, vanpool, school bus, paratransit, airplane, ferry, taxi, and motorcycle. These modes were infrequently observed in the survey; removing those modes from the analysis only reduced the dataset by 104 observations.

The final datasets were still sizeable, despite filtering by multiple dimensions. Ultimately, 6,721 work trips and 21,481 non-work trips were included in the analysis.

Land Use Data

The trip data includes trip origins and destinations at the travel analysis zone (TAZ) level, of which there are 3,600 in the four-county PSRC region. The 2014 land use data for each TAZ is used in the generation of their base year model, and they maintain a separate land use forecasting model to project land use scenarios for long-range planning. This analysis used the 2014 base data.

Land use features included: total employment, number of households, number of university students, average price of public off-street parking spaces on a parcel with per-hour pricing, and square footage. From these fields, we can derive employment density, household density, and university student density, three characteristics that would likely serve as reasonable proxies for the "5Ds" of land use: density, diversity, design, destination accessibility, and distance to transit (Ewing & Cervero, 2010). These land use factors were joined to the trip table based both on trip origins and destinations in order to distinguish between the impacts that such variables would have unique to each trip end.

Google Maps Directions API

As previously discussed, a mode choice model requires not only information about travel time and cost of the observed mode choice but those of unobserved, unchosen modes in the choice set. In order to estimate those counterfactual level-of-service variables, this analysis used a limited-availability data source from the Google Maps Platform.

The Google Maps platform provides the Directions API as a service that calculates directions between locations. After specifying origin and destination coordinates, time of day, and mode, the API returns the most efficient travel route by optimizing travel time. The travel time is based on a proprietary traffic model that is Google's best estimate of travel time given historical traffic conditions and live traffic; they provide few insights to their prediction methodology. The different travel modes that can be requested include driving, walking, bicycling, and transit (Google Developers, 2019). One limitation is that one cannot use the API to distinguish differences between single occupancy vehicle and high occupancy vehicle travel times that may occur due to the availability of high occupancy vehicle lanes on highways. The following section describes how this issue was addressed using PSRC travel model data. Another limitation is that one cannot distinguish between different modes of transit, such as local bus or rail. This is unideal, but not a major issue because the mode choice analysis was simplified by grouping all transit modes in a single category even though there are likely distinct behaviors associated with various forms of transit. Another limitation is that one cannot request historic travel times from the API, only future travel times. Therefore, collecting travel time data from the API in late 2018 creates a mismatch in time and season.

PSRC Travel Model Skims

PSRC maintains a network traffic assignment model. They provided its skim data, or the traffic assignment model outputs, which provide estimates of network travel time from TAZ to TAZ by mode and by time of day (Bowman, 2014). For each private automobile trip in the observed trip dataset, the proportional change in travel time from single occupancy vehicles and high occupancy vehicles was estimated using the network skims. Then, Google Maps Directions API data was scaled to generate estimated private shared automobile travel times under the assumption that the Google Maps data was estimated on the basis of a single occupancy vehicle.

Historic Gas Price Data

Finally, to estimate the cost of travel, which was not collected by PSRC's survey, historic gas price data from the US Energy Information Administration was used (US Energy Information Administration, 2019). They report weekly retail gasoline prices per gallon for the Seattle region, so an average regional cost per gallon was mapped to each automobile trip based on the week of travel. This analysis assumed an average fleet fuel economy of 22 miles per gallon based on the Bureau of Transportation Statistics' Average Fuel Efficiency of Light Duty Vehicles data in 2016. Then, based on automobile trip length, the cost of gasoline was used to estimate the total cost of travel. If the ride was shared by multiple people, the total cost was divided by the number of total travelers. This analysis did not consider the cost of insurance or the vehicle itself.

Discrete Choice Models

Previous literature has found that trips made with ridesourcing are more likely be made for recreational and social purposes than for work purposes. Various personal and trip level-of-service factors that influence a person's decision to choose to ridesource likely have different impacts given a particular trip's purpose. For instance, a person who is considering using ridesource to get to work may be more influenced by the expected travel time than a person who is considering using ridesource to reach a social activity, as the commute trip may have a higher penalty for showing up to work late. The trip mode choice decision-making process between work and non-work trips is likely distinct enough to demand separate model functional forms in order to best isolate the impacts on travel mode choice by various regressors (Handy, 1996).

Because of the assumption of a shorter time scale, these models are most suitable for evaluating a policy's impact for a time scale of months, rather than years. These models are likely inappropriate for estimating the impact of a pricing policy on travel behavior over longer time periods, as in that time an individual may make long-term choices that influence their travel behavior, such as residential location, destination choice, employment location, and vehicle ownership. The models did not consider time of day of travel, residential location, destination choice, workplace location, vehicle ownership, or other commonly modeled choice dimensions, and thus cannot evaluate whether policies influence when people choose to travel, where people choose to live or work, or how many vehicles a person chooses to own, even if these choices are ultimately interrelated.

This analysis applied McFadden's choice model to estimate both mode choice models. This is a generalization of the conditional logit model which can allow for two types of independent variables, alternative-specific and case-specific. Given a choice model with numerous possible choices, alternative-specific variables vary across alternatives such as travel cost and travel time. Case-specific variables vary only for individuals such as household income or vehicle ownership (McFadden, 1973).

The mathematical structure of the alternative specific conditional logit estimates the probability that an individual will choose each alternative in their choice set, or set of individual-specific alternatives. Not all individuals in the data set must have the same choice set. This analysis makes assumptions about individuals' choice sets. First, it assumed that people who reside in zero-vehicle households did not have driving alone in their choice set. Second, it assumed people that had never used ridesourcing did not have ridesourcing in their choice set. Third, it assumed that trips where the Google Maps Direction API showed no results for transit, walking, or biking did not have the corresponding mode in their choice set.

Koppelman and Bhat delivered *A Self Instruction Course in Mode Choice Modeling: Multinomial and Nested Logit Models* to the Federal Transit Administration. Their presentation of the methods and applications of disaggregate models for modeling decision making in a travel behavior context have been invaluable, and the following discussion of relevant methods is largely a summary of their work.

The probability of choosing an alternative *i* from a set of J alternatives is calculated based on the following expression:

$$P(i) = \frac{\exp(V_i)}{\sum_J \exp(V_j)}$$

Here, V_i is the utility of alternative *i,* which is a linear combination of the aforementioned alternative-specific and case-specific independent variables. To illustrate, a small example of a set of utility functions within a three-choice model of drive alone (DA), shared (SR), and transit (TR) follows. These utilities include a deterministic portion of utility, V_i, and a probabilistic portion, ε_i.

$$U_{DA} = V_{DA} + \varepsilon_{DA} = \beta_{traveltime} * TT_{DA} + \beta_{income,DA} * income + \varepsilon_{DA}$$

$$U_{SR} = V_{SR} + \varepsilon_{SR} = \beta_{traveltime} * TT_{SR} + \beta_{income,SR} * income + \varepsilon_{SR}$$

$$U_{TR} = V_{TR} + \varepsilon_{TR} = \beta_{traveltime} * TT_{TR} + \beta_{income,TR} * inc + \beta_{waittime,TR} * wait + \varepsilon_{TR}$$

There are two features of the above utility functions worth noting. First, the coefficient for travel time is the same for all modal utility functions. This is a default model specification for alternative-specific variables such as modal travel time, but it is technically feasible to estimate mode-specific coefficients here as well. Second, the coefficient for case-specific variables such as income and transit wait time is unique to each utility function.

There are three critical assumptions which we must accept in order to estimate the coefficients of the utility functions. The first is that the error terms follow an extreme value distribution. The second is that the errors are identically and independently distributed among alternatives. The third is that the error components are identically and independently distributed across individuals. Under these assumptions, we can use maximum likelihood estimation methods to estimate the parameters which make up the utility functions (Koppelman & Bhat, 2006).

A tool for interpreting these types of models is a measure of the response in choice probabilities due to a change in isolated variables. Especially in the case of a multinomial logit, a raw coefficient is not that informative about how a variable impacts the probabilities of each choice. A marginal effect of a variable is the expected change in percentage of probability of a choice in response to a unit increase in a variable. The marginal effect is useful for making predictions. In interpretation of alternative specific conditional logit models, we may wish to evaluate the impact of changing the attributes of only one of multiple alternatives. In that case, marginal effects as a result of this isolated change can be calculated for both the probability of the changed alternative and all other alternatives. For instance, if only driving alone is made more expensive (perhaps through congestion pricing), we would be able to predict how the mode share of each alternative changes in response. These marginal effects for continuous variables can be estimated using the first derivative of the probability. For the direct marginal effect of a change of a specific alternative on that alternative, the direct derivative is:

$$\frac{\partial P_i}{\partial X_{ik}} = \left(\frac{\partial V_i}{\partial X_{ik}}\right)(1 - P_i)(P_i) = \beta_k(1 - P_i)(P_i)$$

where P_i is the probability of alternative i given some specific value for each attribute, V_i is the alternative-specific utility function, β_k is the estimated coefficient on the attribute, and X_{ik} is the k^{th} attribute of alternative i.

The cross-derivative estimates the effect of a change in one alternative's attributes on the probability of other alternatives:

$$\frac{\partial P_j}{\partial X_{ik}} = -\beta_k(1 - P_i)(P_j)$$

where P_j is the probability of alternative j given some specific value for each attribute.

Marginal effects can also be estimated for discrete variables such as logical ones that only take either zero or one. In that case the marginal effects are:

$$\frac{\Delta P_i}{\Delta X_{ik}} = P(Y_i = 1|X_k = 1) - P(Y_i = 1|X_k = 0)$$

$$\frac{\Delta P_j}{\Delta X_{ik}} = P\left(Y_j = 1\middle|X_k = 1\right) - P\left(Y_j = 1\middle|X_k = 0\right)$$

Most notable about the marginal effects of variables in a logit model is that the effect depends on what values for each attribute are under consideration. Commonly the sample mean or median is used to summarize marginal effects, but the analyst can actually use any value. The policy analysis in Chapter 5 demonstrates how the marginal effect of travel cost is experienced by travelers of different population segments by varying attribute values for the same policy change. This analysis used the Stata software package to perform both the model estimation and marginal effects estimation.

Work Travel Mode Choice Model

There are 6,721 work trips made that start or begin in zip codes where ridesource trips are observed. The data set only includes home-based work trips, eliminating trips which are technically to or from a place of work but distinct from habitual commute trips, such as walking to a restaurant for lunch. Characteristics of these trips are summarized in the following table, including those of the individual making the trip, the household to which that individual belongs, and the trip itself.

Variable	Count	%
Age		
Under 5 years old	23	0.34
5-11 years	17	0.25
12-15 years	12	0.18
16-17 years	7	0.10
18-24 years	474	7.05
25-34 years	3100	46.12
35-44 years	1603	23.85
45-54 years	774	11.52
55-64 years	557	8.29
65-74 years	136	2.02
75-84 years	18	0.27
Income per Household Member		
Under 28,000	947	14.09
$28,000 - $56,000	2145	31.91
$56,000 - $84,000	1728	25.71
$84,000 - $112,000	853	12.69
$112,000 - $140,000	822	12.23
$140,000 or more	226	3.37
Household Vehicle Count		
Zero	929	13.82
One	3559	52.95
Two	1905	28.34
Three or more	328	4.88
Number of Household Adults		
One	2067	30.75
Two	4318	64.25
Three	239	3.56
Four or more	97	1.44
Number of Household Children		
Zero	5617	83.57

One	660	9.82
Two or More	444	6.61
Household Density at Trip Origin		
Under 7,300 households/sqmi	3872	57.61
7,300 – 14,600 households/sqmi	1498	22.29
14,600 – 21,900 households/sqmi	652	9.70
21,900 households/sqmi or more	689	10.41
Employment Density at Trip Destination		
Under 10,000 jobs/sqmi	3077	45.85
10,000 – 20,000 jobs /sqmi	991	14.77
20,000 – 30,000 jobs /sqmi	619	9.22
30,000 – 40,000 jobs /sqmi	500	7.45
40,000 – 50,000 jobs /sqmi	265	3.95
50,000 – 60,000 jobs /sqmi	209	3.11
60,000 jobs /sqmi or more	1050	15.65
Average Off-Street Parking Cost at Destination		
$0	5050	75.14
Under $10/hr	171	2.54
$10-$20/hr	377	5.61
$20-$50/hr	468	6.96
$50-$100/hr	655	9.75
$100/hr or more		
Time of Day		
5AM to 9AM	2723	40.51
9AM to 3PM	1415	21.05
3PM to 7PM	2042	30.38
7PM to 2AM	479	7.13
2AM to 5AM	62	0.92
Trip Ends		
Into Seattle	422	6.28
Out of Seattle	858	12.77
Within Seattle	4036	60.05
Outside Seattle	1405	20.90

Table 6: Summary of Individual and Trip-Level Characteristics of Work Trip Data

Most travelers in this data set are between 25 and 44 years of age and come from households with $28,000 to $84,000 of income per household member, at least one vehicle, two adults, and no children. Most trips originate from low household density areas and end in areas where average off-street parking costs are low.

Mode	Count	%
Drive Alone	2896	43.09
Shared Ride	478	7.11
Ridesource	98	1.46
Transit	1917	28.52
Walk	943	14.03
Bike	389	5.79

Table 7: Observed Work Mode Choice

Of the six modes of interest, the most common work trip mode choice was driving alone, followed by transit. This data set was used to estimate the utility function parameters of the following alternative specific conditional logit model of work mode choice.

Variables	Work Trip Mode (base: Shared Ride)									
	Drive Alone		Ridesource		Transit		Walk		Bike	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Level of Service										
Distance (walk)	--	--	--	--	--	--	-0.686	-14.47	-0.046	-2.11
Cost	-0.116	-6.67	-0.116	-6.67	-0.116	-6.67	-0.116	-6.67	-0.116	-6.67
Travel Time	-0.013	-7.35	-0.013	-7.35	-0.013	-7.35	-0.013	-7.35	-0.013	-7.35
Socio-demographics										
Age	0.326	7.79	0.340	3.33	0.272	5.90	0.218	4.10	0.256	4.51
Income per Person	$3.6*10^{-6}$	2.33	$6.8*10^{-6}$	2.52	$3.0*10^{-6}$	1.90	$6.2*10^{-6}$	3.64	$1.2*10^{-5}$	5.89
Household										
No. Adults	-0.467	-5.17	--	--	--	--	--	--	0.349	3.01
No. Children	-0.378	-5.37	--	--	-0.550	-6.11	-0.649	-4.96	0.392	4.17
No. Workers	-0.568	-7.01	--	--	--	--	--	--	--	--
Vehicle Count	0.570	7.28	-0.877	-5.06	-0.700	-8.99	-0.799	-8.21	-0.634	-5.66
Land Use										
HH Density (Origin)	--	--	--	--	$1.8*10^{-5}$	5.43	$1.8*10^{-5}$	4.48	--	--
Emp. Density (Dest.)	$-2.2*10^{-6}$	-4.19	--	--	$1.0*10^{-6}$	3.08	--	--	--	--
Parking Cost (Origin)	-0.003	-2.22	0.004	2.81	0.005	4.44	0.004	3.35	0.003	2.39
Parking Cost (Dest.)	-0.003	-2.98	--	--	0.002	2.54	0.002	2.82	--	--
Trip Attributes										
Into Seattle	0.467	2.05	1.336	1.57	2.210	8.67	1.729	2.36	0.231	0.29
Out of Seattle	0.722	4.19	2.770	4.62	2.226	10.17	3.416	6.10	0.967	1.94
Within Seattle	0.358	2.98	2.044	4.83	1.937	12.10	1.021	6.35	2.633	10.77
9AM to 3PM	0.288	3.03	--	--	-0.281	-2.57	--	--	-0.375	-2.34
3PM to 7PM	--	--	--	--	--	--	0.213	1.98	--	--
7PM to 2AM	--	--	1.477	5.69	--	--	--	--	-0.666	-2.41
2AM to 5AM	1.766	4.18	1.774	2.24	--	--	--	--	--	--
Constant	0.424	1.31	-3.312	-4.30	-0.800	-2.34	1.096	2.81	-4.077	-7.92

Table 8: Work Trip Model Choice Estimation Results

Higher income is associated with using ridesource for work trips rather than shared rides, or carpooling. Having more household vehicles is associated with a lower probability of using ridesource. A higher parking cost at the trip origin is also associated with a higher likelihood of using ridesourcing rather than carpooling. Trips out of Seattle and within Seattle are more likely to use ridesourcing rather than carpooling. Finally, trips between 7PM and 5AM are more likely use ridesourcing than carpooling. The direction of these findings are reasonable, as previous studies have found through surveys that people who are more likely to use ridesourcing are higher income, live in denser areas and own fewer vehicles, often cite the cost of parking as a reason to avoid driving themselves to a destination, and take trips at night.

The coefficients of multinomial logit and related models can be tricky to interpret directly. With a simpler model, like a linear regression or a binary logit, the sign of an estimated coefficient is always the same sign as the marginal effect of that variable. For instance, in a binary logit model if the coefficient on cost is negative, then we know that a unit increase in cost is associated with a decrease in the probability of the alternative in question. However, in the case of a multinomial logit model, it is possible that the sign of a coefficient could be opposite of that of the marginal effect. Therefore, it is informative to summarize the marginal effects of multinomial logit models alongside the estimated coefficients. The following summarizes the own- and cross-elasticities of the probability of each choice relative to a unit increase in cost for vehicle-based modes (drive alone, shared ride, and ridesource).

Alternatives	**Marginal Effect of Cost (at Means)**					
	Drive Alone		Shared Ride		Ridehail	
	$\partial P/\partial X$	z-stat	$\partial P/\partial X$	z-stat	$\partial P/\partial X$	z-stat
Drive Alone	-0.0261	-6.60	0.0121	5.99	0.0004	2.43
Shared Ride	0.0121	5.99	-0.0155	-6.09	0.0001	2.37
Ridesource	0.0004	2.43	0.0001	2.37	-0.0006	-2.43
Transit	0.0116	5.79	0.0028	5.19	0.0001	2.35
Walk	0.0006	4.10	0.0001	3.85	$4.5*10^{-6}$	2.17
Bike	0.0014	3.73	0.0003	3.55	$1.1*10^{-5}$	2.12

Table 9: Marginal Effects of Travel Costs on Work Trip Mode Choice Probabilities

The marginal effects evaluated at the mean of all attributes suggests how changing travel cost could impact mode choice. This summary could be tailored for different trip types and traveler demographics. Here we can see that if the cost of driving alone was increased by one dollar for all trips in the analysis region, 2% of people who had previously driven alone would choose other modes. The model predicts that 46% of those who switch would next choose a shared ride or carpool, 44% would next choose transit, and the remaining 10% shared between bicycling, walking, and ridesourcing. This could suggest that a congestion fee on single occupancy vehicles may primarily encourage mode shifts towards carpooling and transit, although this analysis has not yet refined the scope to only include the marginal effect of cost on trips into and within Seattle, where a congestion fee would most likely be implemented.

For a one dollar increase in the cost of the average ridesourcing trip, the model predicts that just 0.06% of trips would switch to other modes. This may suggest that ridesourcing work trips are significantly less price-sensitive than driving by personal vehicle, either alone or in a carpool. We also observe that 66% of those shifted trips would move to driving alone, while 16% would switch to shared rides, 15% to transit, and the remaining 3% to either walk or bicycling. The first implication of this is that a fee on TNC trips is unlikely to curtail congestion caused by ridesourcing, as these trips seem to be relatively price-inelastic. However, we also need to consider where and when these trips are taking place; for instance, if TNC trips during peak hours in Seattle are much more price-elastic, and people are likely to switch to mass or non-motorized modes, then perhaps a TNC fee alone could offer congestion reduction benefits. Also, it seems that ridesourcing trips are not competing heavily with transit, at least over work trips. If there was more competition between the two modes, we might expect to see that increase in ridesource cost might lead to many people switching to transit as a next best option. Again, this marginal effect could be different for different segments of the population, and Chapter 5 examines some of the variations in response within the population.

Non-work Travel Mode Choice Model

There are 13,279 home-based non-work trips used in the following estimation of a non-work mode choice model. Distributions of relevant traveler and trip attributes in this data set are summarized.

Variable	Count	%
Age		
Under 5 years	745	5.61
5-11 years	526	3.96
12-15 years	133	1.00
16-17 years	40	0.30
18-24 years	687	5.17
25-34 years	4433	33.38
35-44 years	2892	21.78
45-54 years	1586	11.94
55-64 years	1089	8.20
65-74 years	840	6.33
75-84 years	275	2.07
Over 84 years	33	0.25
Income per Household Member		
Under 28,000	2260	17.02
$28,000 - $56,000	4769	35.91
$56,000 - $84,000	3293	24.80
$84,000 - $112,000	1366	10.29
$112,000 - $140,000	1248	9.40
$140,000 or more	343	2.58
Household Vehicle Count		
Zero	1693	12.75
One	6364	47.93
Two	4513	33.99
Three or more	709	5.34
Number of Household Adults		
One	3604	27.14
Two	9258	69.72
Three	298	2.24
Four or more	119	0.90
Number of Household Children		
Zero	8949	67.39
One	2232	14.14
Two or More	1998	15.81
Household Density at Trip Origin		
Under 7,300 households/sqmi	7977	60.07

7,300 – 14,600 households/sqmi	2911	21.92
14,600 – 21,900 households/sqmi	1163	8.76
21,900 households/sqmi or more	1228	9.25
Employment Density at Trip Destination		
Under 10,000 jobs/sqmi	7967	60.09
10,000 – 20,000 jobs /sqmi	2008	15.15
20,000 – 30,000 jobs /sqmi	868	6.55
30,000 – 40,000 jobs /sqmi	887	6.69
40,000 – 50,000 jobs /sqmi	507	3.82
50,000 – 60,000 jobs /sqmi	284	2.14
60,000 jobs /sqmi or more	737	5.56
Average Off-Street Parking Cost at Destination		
$0	11443	86.17
Under $10/hr	474	3.57
$10-$20/hr	295	2.22
$20-$50/hr	401	3.02
$50-$100/hr	341	2.57
$100/hr or more	325	2.45
Time of Day		
5AM to 9AM	1387	10.45
9AM to 3PM	4131	31.11
3PM to 7PM	4754	35.80
7PM to 2AM	2974	22.40
2AM to 5AM	33	0.25
Day of Week		
Weekday	10070	75.83
Weekend	3209	24.17
Trip Ends		
Into Seattle	304	2.29
Out of Seattle	616	4.64
Within Seattle	8666	65.26
Outside Seattle	3693	27.81
Trip Purpose		
Social/Recreational	5431	40.90
Maintenance/Shopping	7848	59.10

Table 10: Summary of Individual and Trip-Level Characteristics of Non-Work Trip Data

Most travelers in this non-work trip data set are between the ages of 25 and 54, and come from households where the income per household member is between $28,000 and $84,000 a year, there is at least one household vehicle, two household adults, and no household children. Most trips in this data set originate in TAZs with fewer than 7,300 households per square mile, end in TAZs with fewer than 10,000 jobs per square mile and have no off-street parking cost, take place between 9AM and 7PM, on weekdays, within Seattle, and for maintenance or shopping purposes.

Mode	Count	%
Drive Alone	3764	28.35
Shared Ride	4981	37.51
Ridesource	221	1.66
Transit	772	5.81
Walk	3291	24.78
Bike	249	1.88

Table 11: Observed Non-Work Mode Choice

There are differences in mode split between work trips and non-work trips, supporting the decision to model these trips separately. Relatively more work trips are taken using transit (28% as compared to 6%), driving alone (43% as compared to 28%) and bicycling (6% as compared to 2%). Relatively more non-work trips are taken using shared rides (38% as compared to 7%) and walking (25% as compared to 14%). Ridesource mode split is roughly equivalent for both trip types, at either just above or below 1.5% of total mode share.

Variables	**Non-Work Trip Mode (base: Shared Ride)**									
	Drive Alone		Ridesource		Transit		Walk		Bike	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
Level of Service										
Distance (walk)	--	--	--	--	--	--	-3.020	-38.84	--	--
Distance (bike)	--	--	--	--	--	--	--	--	-0.934	-17.39
Cost	-0.198	-7.70	-0.198	-7.70	-0.198	-7.70	-0.198	-7.70	-0.198	-7.70
Travel Time	-0.013	-46.76	-0.013	-46.76	-0.013	-46.76	-0.013	-46.76	-0.013	-46.76
Socio-demographics										
Young (<25 years)	-0.419	-7.49	--	--	-0.834	-4.42	-0.214	-2.44	-0.449	-2.66
Elderly (>65 years)	-0.668	-4.27	--	--	--	--	--	--	-1.274	-1.71
Income per Person	$2.1*10^{-6}$	2.91	$5.3*10^{-6}$	2.96	$-9.7*10^{-6}$	-4.37	$1.6*10^{-6}$	1.66	--	--
Household										
No. Adults	-1.273	-21.99	--	--	--	--	--	--	--	--
No. Children	-1.079	-27.18	-1.285	-6.07	-0.905	-5.37	-0.394	-7.33	--	--
No. Workers	--	--	--	--	-0.527	-4.25	-0.219	-3.78	-0.391	-3.67
Vehicle Count	0.410	9.81	-1.618	-11.53	-0.846	-6.80	-0.431	-7.67	--	--
Land Use										
HH Density (Origin)	$-5.4*10^{-6}$	-1.91	--	--	$3.1*10^{-5}$	4.57	$7.0*10^{-6}$	1.82	--	--
HH Density (Dest.)	--	--	$1.2*10^{-5}$	1.85	$2.8*10^{-5}$	4.29	$1.3*10^{-5}$	3.26	--	--
Emp. Density (Origin.)	--	--	$1.9*10^{-6}$	3.30	$1.4*10^{-6}$	3.62	--	--	--	--
Emp. Density (Dest.)	$-1.2*10^{-6}$	-2.72	$3.4*10^{-6}$	6.84	--	--	--	--	--	--
Parking Cost (Origin)	--	--	0.003	1.73	--	--	-0.004	-4.97	-0.013	-3.54
Parking Cost (Dest.)	--	--	-0.005	-2.00	0.008	7.53	--	--	--	--
Trip Attributes										
Into Seattle	--	--	2.318	4.14	-5.031	-4.60	--	--	--	--
Out of Seattle	--	--	--	--	-2.776	-3.02	2.432	3.26	--	--
Within Seattle	0.133	2.61	1.514	4.84	0.712	1.82	0.218	2.44	0.834	3.94
9AM to 3PM	0.609	9.89	2.221	2.77	--	--	--	--	--	--
3PM to 7PM	0.143	2.42	1.995	2.49	0.710	3.86	--	--	--	--
7PM to 2AM	--	--	2.849	3.59	-1.139	-4.70	-0.427	-4.60	-0.583	-3.09
2AM to 5AM	1.138	2.25	5.449	5.31	--	--	--	--	--	--
Weekend	-0.794	-13.00	-0.457	-2.62	-0.909	-4.05	-0.336	-3.62	-0.527	-2.76
Social Purpose	-0.303	-5.97	1.418	7.22	-0.700	-4.19	--	--	--	--
Constant	2.080	15.40	-4.170	-4.65	-2.438	-5.33	2.131	12.87	-2.765	-11.11

Table 12: Non-Work Trip Model Choice Estimation Results

Ridesource trips are more likely to be made by higher income travelers relative to shared rides, and by travelers who have fewer household children and vehicles. Ridesource trips are more likely than shared ride trips to begin and end in high density areas, measured by both household density and employment density. Additionally, ridesource trips are more likely to occur relative to shared ride trips at every time of day except during morning hours from 5AM to 9AM. Finally, ridesource trips are more likely to occur on weekdays and for social purposes rather than maintenance purposes relative to shared ride trips. Again, it is important to be cautious when interpreting the coefficients of multinomial logit models because the sign on a coefficient is not necessarily in the same as the elasticity or marginal effect that the associated attribute has on choice probability.

Alternatives	**Marginal Effects (at Means)**					
	Drive Alone		Shared Ride		Ridehail	
	$\partial P/\partial X$	z-stat	$\partial P/\partial X$	z-stat	$\partial P/\partial X$	z-stat
Drive Alone	-0.0488	-7.69	0.0476	7.67	$1.3*10^{-5}$	1.16
Shared Ride	0.0476	7.67	-0.0486	-7.69	$1.0*10^{-5}$	1.16
Ridesource	$1.3*10^{-5}$	1.16	$1.0*10^{-5}$	1.16	$-2.3*10^{-5}$	-1.16
Transit	0.0009	2.39	0.0007	2.37	$1.9*10^{-7}$	1.05
Walk	$4.2*10^{-5}$	4.08	$3.2*10^{-5}$	3.93	$8.9*10^{-9}$	1.12
Bike	0.0003	3.84	0.0002	3.72	$5.4*10^{-8}$	1.12

Table 13: Marginal Effects of Travel Costs on Non-Work Trip Mode Choice Probabilities

Based on these marginal effects, for every dollar increase in cost of driving alone, those that shift away from drive alone would mostly likely next choose a shared ride or carpool. Those that shift away from shared ride due to a cost increase of shared ride trips would most likely choose driving alone. Those that shift away from ridesource due to a cost increase of ridesource trips would most likely split between driving alone and a shared ride. This suggests that those who choose private motorized modes today (driving alone, shared rides, or ridesourcing) for non-work trips are not likely to switch to mass transit or active modes if the cost of travel is increased. This could imply that fees or road pricing be imposed might only produce mimor VMT reductions if people choose higher-occupancy, but still private vehicle-based modes.

Model Findings

This chapter presents two mode choice models estimated under an alternative specific conditional logit model. The analysis segmented the trip data set into work trips and non-work trips because these two types of trips are subject to fundamentally different decision-making processes. This is confirmed by the distinctions between both the magnitude and significance of estimated utility function parameters and the marginal effects of work and non-work trips.

Non-work drive alone and shared ride trips are more sensitive to cost than work trips are (4% as compared to 2% and 4% as compared to 1%-point decrease in choice probability for every dollar increase, respectively), while non-work ridesource trips are less sensitive to cost than work trips (0.002% as compared to 0.06%-point decrease in choice probability). If a flat TNC fee was enacted, work trip modes would likely experience greater shifts than non-work trip modes, whereas under congestion pricing of all private automobiles, non-work trip modes would experience greater shifts than work trip modes.

Increasing the cost of work travel is more likely to produce multimodal behavior than an equivalent increase in the cost of non-work travel. Across all private, motorized modes (drive alone, shared ride, and ridesourcing) between 16% to 50% of travelers that shift from one of these modes for a work trip would choose to take transit instead. However, of non-work trips made by private, motorized modes, only 1% of shifted travelers would switch to transit in lieu of their original mode choice. This suggests that ridesourcing competes with transit more for work trips than it does for either social or recreational non-work trips in the Seattle-Tacoma region. This may be because transit mode share is higher for work trips than it is for other types of trips, and therefore most transit trips are likely made by people traveling for work or commuting purposes. As a result, the entrance of a competitive mode (ridesourcing) is likely to shift more work travel away from transit than it is non-work travel simply by virtue of the relative frequencies of each trip type. Also, work travelers that use transit may either not own cars or work in areas where it would not be convenient to park a personal vehicle during their working hours. Thus, ridesourcing is competitive for those who are seeking a mode to work faster than transit but would enable them to forgo driving themselves. It is also possible that those who choose ridesourcing for social trips or chores have distinct motivations from those who choose transit for social or chores-related purposes. For instance, someone who uses ridesourcing for chores may do so because it requires them to transport items with them, and so transit could be less likely to be an alternative mode than other private vehicle-based modes like driving alone and shared rides. On the other hand, someone who is using transit for chores or socializing is more likely a captive transit rider than someone who uses transit for commuting, and may be less likely to be able to afford habitual or frequent ridesource trips. Under such conditions, those who are observed to use ridesource for social and chore-related purposes would not be likely to choose transit in place of ridesourcing, and those who originally chose transit may not be able to replace transit with ridesourcing; neither of these hypothetical types of travelers would be comparing ridesourcing and transit directly.

Chapter 5: Cordon Pricing Policy Analysis

This chapter examines the following research questions: how would cordon pricing impact congestion, equity, multimodality, and emissions in the Greater Seattle region, and how should its associated revenue be spent? I hypothesize that differences in where cordon pricing revenue is spent both programmatically and geographically will vary transportation system outcomes due to regional travel behavior impacts. The following analysis evaluates whether spending across the region and across modes advance Seattle's local equity, congestion relief, and emissions reductions goals more than if investments were concentrated in Seattle. This could provide justification for allocating some or all of the cordon pricing revenue for transit service improvement and expansion by Sound Transit and King County Metro, as this would simultaneously advance local and regional goals.

First, we establish current conditions based on the aforementioned metrics and compare the impact of each scenario relative to current conditions. Then, the relative merits and trade-offs of each scenario are discussed. These findings are used to assess whether cordon pricing in Center City in general deserves further consideration, and whether a particular revenue investment scenario is superior.

CURRENT CONDITIONS

King County is selected as the study area because it contains nearly all trips likely to be impacted by cordon pricing in Center City Seattle, all of King County Metro's transit service, and the majority of Sound Transit's transit service. Even though cordon pricing would likely be limited to Center City Seattle, it attracts trips from all over the Seattle-Tacoma region, including King County and the rest of Seattle.

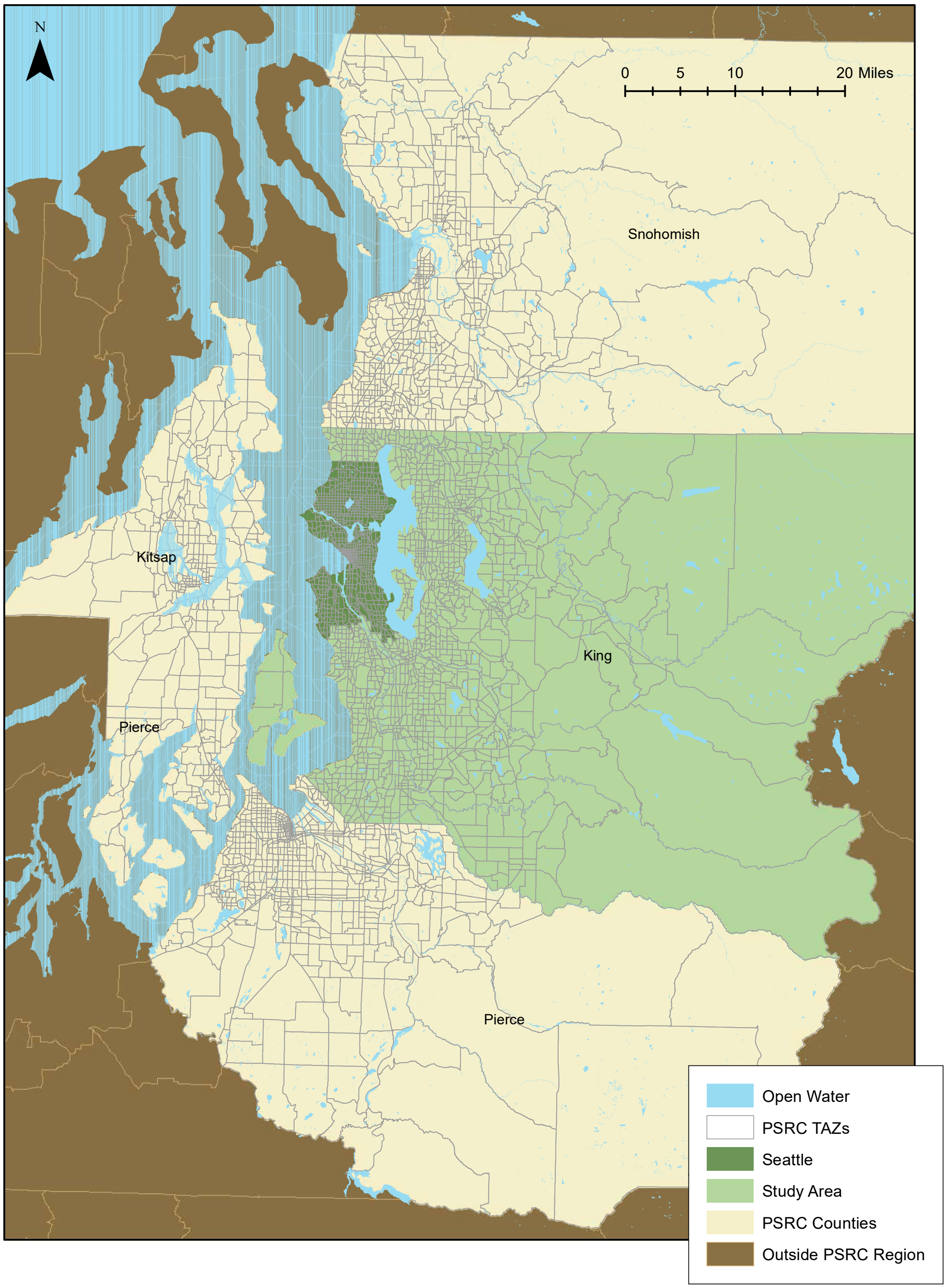

Figure 6: Policy Analysis Study Area within PSRC Region

The study area contains 2,145 of the 3,700 traffic analysis zones (TAZs) in the PSRC region. King County is home to 2.2 million residents, 850,000 households, and 1.3 million employees. It covers approximately 1,290 square miles.

The following tables summarize estimated present-day traffic demands and mode shares throughout the study region, segmented by geography, time of day, individual-level demographics such as household income and vehicle ownership, and zonal-level demographics such as housing and transportation affordability and average household greenhouse gas emissions. Segmentation enables the evaluation of cordon pricing schemes against Seattle's strategic goals in equity, congestion management, expanded transportation options, and greenhouse gas emissions reduction as well as regional strategic goals for expanding transit system service.

The 2014 Puget Sound Regional Council origin-destination trip tables generated by their 4-step traffic model provide estimates of traffic demand within Center City, Outer Seattle, and King County by time of day. PSRC provide trip tables by mode, trip type (work or non-work), and time of day between each of the 3,600 TAZs in the region. These estimate daily trip counts based on trip generation and trip distribution models, which use a mix of land use and demographic data to model the number of trips attracted to each TAZ, the number of trips produced by each TAZ, and the resulting number of trips between TAZs. Trips are aggregated by geography, time of day, and mode to produce a baseline measure of traffic demand.

			Time of Day		
			Non-peak	AM Peak (6AM – 9AM)	PM Peak (3PM – 6PM)
Location	Work	Center City (Seattle)	3,816	8,014	8,644
		Outer Seattle	11,969	22,776	28,929
		King County	34,542	66,321	84,709
	Non-Work	Center City (Seattle)	20,254	45,633	43,596
		Outer Seattle	64,570	124,982	153,769
		King County	228,018	437,838	560,060

Table 14: Estimated Vehicular Trips per Hour by Time of Day and Location

For each geography there are more work trips per hour during peak travel hours relative to non-peak travel hours. Center City experiences the most dramatic increase in trips per hour from non-peak travel times to peak travel times, likely because many jobs are located in the area and is thus a major trip attractor during peak commute times.

There are more vehicular non-work trips than work trips for every geography and time of day, which could be because the region has roughly twice as many total inhabitants as it does employees. Furthermore, non-work trips are typically shorter and more frequent than work trips. Interestingly, even non-work trips occur more frequently during peak travel times than non-peak travel times, even though these trips are likely more flexible than work trips and could potentially be shifted to different times of the day to avoid recurring traffic congestion during commute hours.

Based on the PSRC trip tables, there are approximately 750,000 daily vehicular trips into, within, or out of Center City, with 660,000 originating from outside of Center City or towards a destination outside of Center City.

Transportation equity has several interpretations, many built upon the concepts of transportation need or ability. The twin concepts of vertical and horizontal equity are commonly used: horizontal equity describes the equal allocation to resources to individuals of equal transportation need, while vertical equity describes the special consideration given to those who demonstrate the highest transportation need (Litman, 2019). This analysis prioritizes the fulfilment of vertical equity, so we prefer policy solutions which provide the most benefit to the members of the population with the highest need for quality public transportation or lowest ability to access transportation. Because transportation need cannot be measured directly, grouping the population by relative need requires choosing reasonable proxies. Two individual-level characteristics that are strongly associated with need and access to transportation are vehicle ownership and income; those with fewer vehicles or lower incomes are more likely to have reduced access to transportation, either because they have reduced automobility or have reduced ability to pay for transportation services. Therefore, the study area population is segmented according to transportation need using vehicle ownership and household income.

Income Percentile			Vehicle Ownership: No Vehicles			Vehicle-Constrained			Vehicle-Abundant		
			Auto	TNC	Transit	Auto	TNC	Transit	Auto	TNC	Transit
Income Percentile	Work	< 25th	6.7	3.9	29.7	42.0	1.1	15.4	63.9	0.8	10.9
		< 50th	3.7	2.4	33.5	51.4	1.5	14.1	58.9	0.9	10.7
		< 75th	3.0	3.2	45.8	37.4	1.7	15.5	62.3	0.8	9.2
		≥ 75th	5.0	3.4	28.7	35.3	2.0	14.4	64.3	0.9	7.9
	Non-Work	< 25th	3.2	1.7	33.1	58.5	1.6	13.3	75.7	0.4	5.5
		< 50th	5.3	2.8	26.3	56.6	2.1	11.3	66.5	0.8	8.3
		< 75th	5.9	4.2	19.7	55.1	2.0	6.5	75.1	0.7	3.9
		≥ 75th	3.9	5.4	22.0	53.5	2.3	8.2	77.7	0.9	3.4

Table 15: TNC, Personal Automobile, and Transit Mode Shares (%) by Income Percentile and Vehicle Ownership

From lowest vehicle ownership levels (no vehicles) to highest vehicle ownership levels (vehicle-abundant households where vehicles are equal to or outnumber driver's license holders), automobility (as measured by automobile mode choice) increases and transit ridership decreases. The relationship between automobility and income is more complex; automobility generally decreases with income for zero-vehicle or vehicle-constrained (fewer vehicles than there are drivers) households and generally increases with income for vehicle-abundant households. This could be explained by household residence or travel preferences, as those who live in denser areas may also choose to have fewer vehicles due to better quality transit service and pedestrian networks, or those who prefer to own fewer vehicles also prefer to drive less. TNC use decreases as household vehicles increase, but is constant with respect to income among zero-vehicle and vehicle-abundant travelers while increasing with income among vehicle-constrained travelers. Finally, transit ridership to work generally decreases with respect to vehicle ownership levels and with respect to income.

For non-work trips, similar trends arise. Automobility increases with vehicle ownership and with income for zero-vehicle and vehicle-abundant households, and decreases with income for vehicle-constrained households. TNC use decreases with vehicle ownership but increases with income. Transit use decreases with vehicle ownership and income.

Another measure of transportation need that can be used to assess the equity of policy outcomes is combined housing and transportation affordability. Measuring their affordability together accounts for the possibility that lower living costs are associated with higher transportation costs or vice versa. Given Seattle's housing affordability crisis, with residents being forced to choose between residential location and travel options, this provides a more comprehensive measure of transportation need than transportation affordability alone. Those who reside in neighborhoods of low housing and transportation affordability are considered to display the highest need for access to affordable transportation, particularly multimodal options. The Center for Neighborhood Technology (CNT, 2017) developed a measure that combines average housing costs, average transportation costs, and average household incomes to assess the combined proportion of income that households spend on housing and transportation.

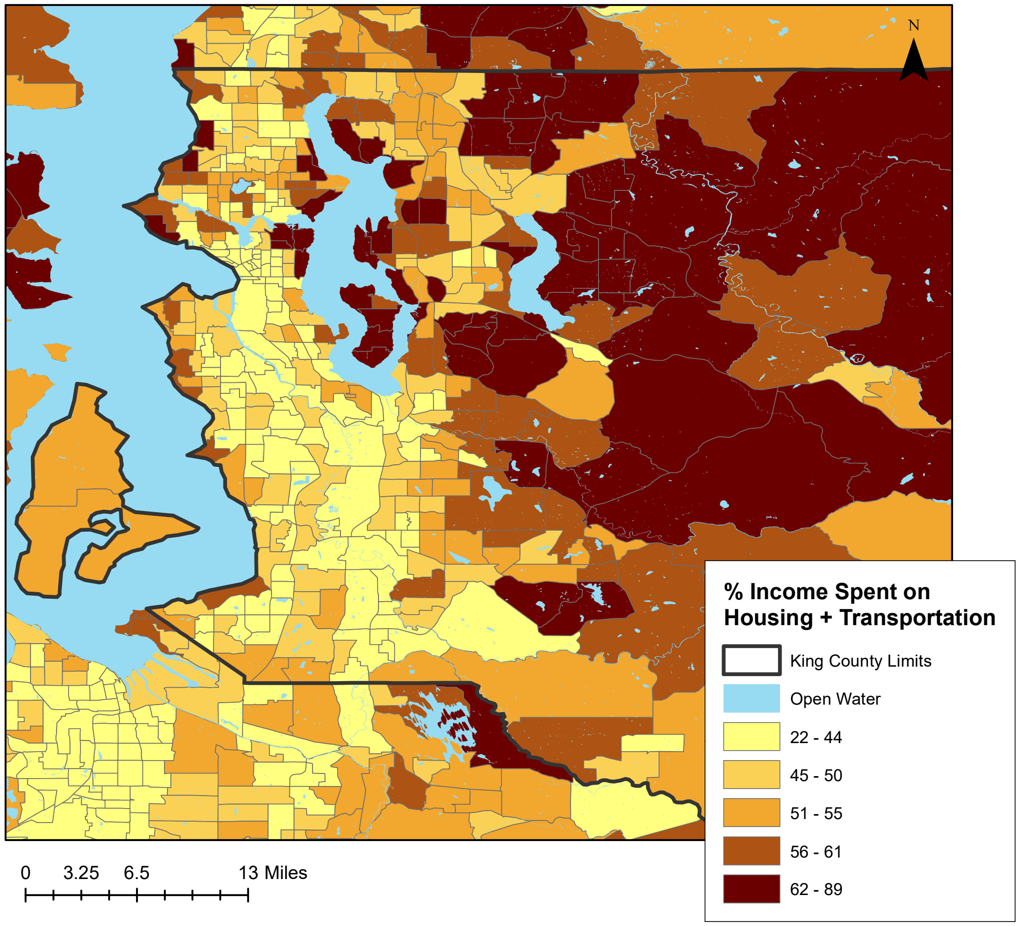

Figure 7: Average Percent of Income Spent on Housing and Transportation Combined by Census Tract

Figure 7 depicts the variation in housing and transportation affordability across the study area. Generally, areas where residents spend the least on household and transportation proportional to their income are located in Seattle. East of Seattle, such as in Bellevue and Redmond, housing and transportation affordability decreases. Even further east in Greater King County, housing and transportation affordability is the lowest, as residents of these census tracts on average spend the highest proportion of their incomes on housing and transportation.

			Mode Share			
			Auto	TNC	Transit	Active
Population-weighted Percentile of Housing + Transportation Affordability (<25th is least affordable)	Work	< 25th	71.9	0.7	20.5	6.9
		< 50th	62.3	0.8	26.4	10.5
		< 75th	56.5	1.1	27.1	15.3
		≥ 75th	35.6	1.9	35.6	26.9
	Non-Work	< 25th	91.7	0.5	4.3	3.5
		< 50th	85.8	1.0	5.1	8.2
		< 75th	77.5	1.2	7.3	14.0
		≥ 75th	55.3	2.8	10.5	31.5

Table 16: Travel Mode Shares (%) by Housing and Transportation Costs as Percent of Income for the Average Census Tract Household

As housing and transportation affordability increases, automobile mode share decreases and TNC, transit, and active mode shares increase. This may be because locations with quality transit services and denser, more walkable neighborhoods are becoming increasingly attractive within the real estate market and attracting higher-income residents. Because these neighborhoods' residents are also higher income, they are more likely to experience higher levels of housing and transportation affordability relative to their income. Those who spend the most of their income on housing and transportation are also more car-dependent. This could motivate the expansion of transit services in those neighborhoods. Automobile use is usually more expensive than transit ridership, so improving transit access and service could alleviate affordability issues for those with the most constrained budgets. However, it is unclear whether it is by choice or by necessity that these lower income households live in areas with low transit access; it is possible that they are automobile-oriented by choice and transit improvements in their area would not inspire them to change modes.

CNT also estimates annual average household greenhouse gas emissions from automobile use in metric tons. Segmenting based on transportation emissions in their neighborhood reveals the travel behaviors of those who emit the most and the least. This implies where transportation improvements may be most effective at reducing automobile use, therefore advancing climate goals. This analysis prioritizes policy solutions which encourage mode shift away from automobile use in high-emitting neighborhoods.

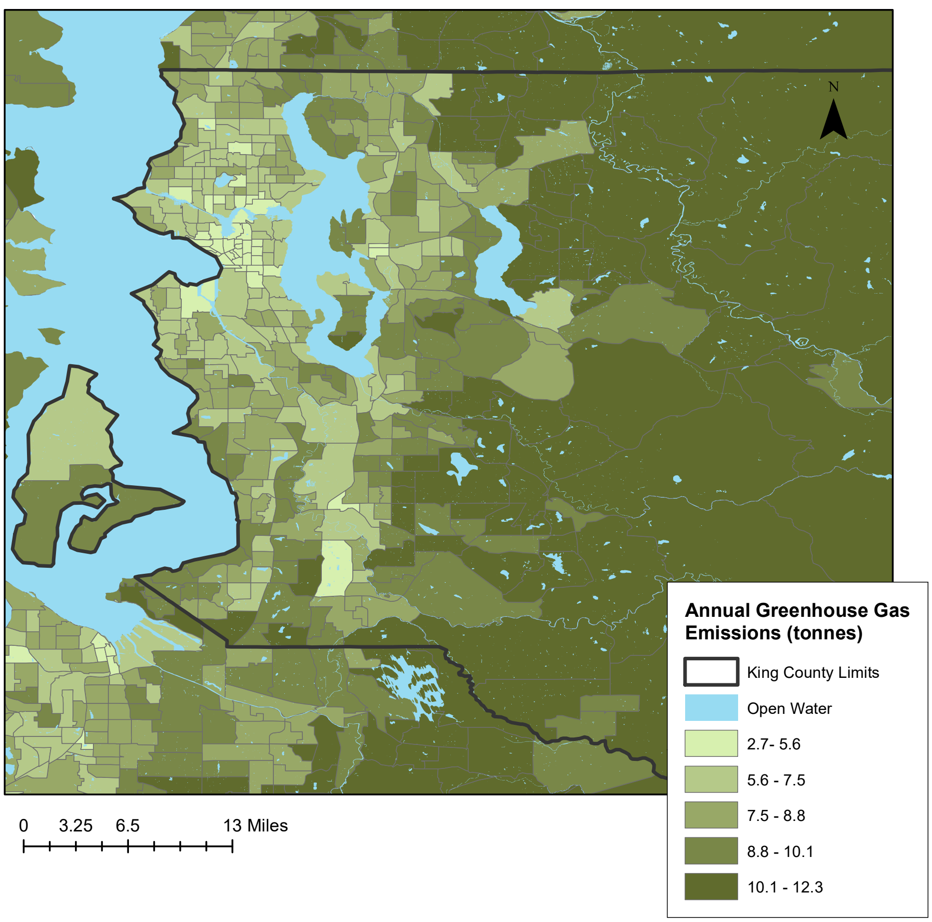

Figure 8: Annual Greenhouse Gas Emissions due to Automobile Use by Census Tract

The census tracts in the study area which emit the least are concentrated within Seattle, Redmond, and Bellevue, while census tracts which emit the most are primarily in eastern King County. This is likely highly correlated with where transit service is available in the region, where dense urban forms encourage walking and bicycling for shorter trips, and where higher income residents can afford to live closer to their places of employment if they so choose.

			Mode Share			
			Auto	TNC	Transit	Active
Population-weighted Percentile of Annual Greenhouse Gas Emissions ($<25^{th}$ percentile is least emitting)	Work	$< 25^{th}$	25.3	2.4	36.8	35.5
		$< 50^{th}$	45.5	1.7	37.5	15.3
		$< 75^{th}$	55.4	1.1	31.6	11.9
		$\geq 75^{th}$	70.3	0.6	22.5	6.6
	Non-Work	$< 25^{th}$	36.8	3.1	10.7	49.4
		$< 50^{th}$	63.5	1.2	10.1	25.2
		$< 75^{th}$	65.5	0.7	7.9	25.9
		$\geq 75^{th}$	85.5	0.3	4.4	9.9

Table 17: Travel Mode Shares (%) by Annual Greenhouse Gas Emissions for Average Census Tract Household

Automobile mode shares are highest and TNC, transit, and active mode shares lowest in the highest-emitting neighborhoods. This corroborates that significant transportation greenhouse gas reductions in the region can be achieved by reducing the automobile use of households that reside in the highest-emitting neighborhoods. Lower-emitting neighborhoods are also associated with higher TNC use. This aligns with the various studies that have suggested that TNCs occupy similar markets as transit. Here it is unclear whether the popularity of ridesourcing in these areas is a consequence of or enables reduced automobile dependency and more environmentally sustainable lifestyles.

Current conditions in the Greater Seattle region do not currently meet policy goals in congestion management, equity, climate action, and multimodal system expansion. Center City in Seattle, Outer Seattle, and greater King County all exhibit tremendous peaks in automobile travel demand during commute hours, which contributes to the severe traffic congestion for which the region is known. Transportation-disadvantaged individuals who are either lower-income, lack private car access, or both have low automobility are the most likely groups to use ridesourcing and transit for both work and non-work travel, which suggests a divide in access and mobility in the region based on one's access to a vehicle. Neighborhoods where housing and transportation affordability is the lowest display the highest level of automobile use, implying that high transportation costs may be driven by lack of available transit options, an outcome that is especially concerning for low-income residents. Finally, the average greenhouse gas emissions by neighborhood varies dramatically throughout the region, with households located near Seattle emitting the least but households outside Seattle emitting four times as much.

ALTERNATIVES ANALYSIS

To determine whether cordon pricing in Center City Seattle can help achieve local and regional strategic goals, and if so, which implementation scenario does so best, we consider two cordon pricing alternatives relative to current conditions. Both scenarios assume a $5 cordon fee to enter Center City by all private automobile and ridesource trips.

In the first scenario, revenue from cordon pricing is used to invest primarily in congestion mitigation in the Center City, which leads to reduced congestion and increased travel speeds for both automobiles and transit in Center City and increased travel speeds in Outer Seattle. This alternative would be realized if Seattle used the revenue from the cordon pricing to improve transit services and to implement a full suite of congestion mitigation measures such as investments in incident management, work zone management, planned special events traffic management, improved traveler information, and advanced adaptive signal systems within Seattle city limits.

In the second scenario, revenue from cordon pricing in Center City is invested throughout King County, emphasizing transit service expansion throughout King County and Outer Seattle. This alternative is possible if significant revenue is spent on Sound Transit and King County Metro service improvements and expansions so that neighborhoods previously lacking transit service or neighborhoods with low frequency service experience increased spatial and temporal transit supply or access.

Both of these scenarios can be modeled within the mode choice modeling framework by altering travel costs and travel times for specific trips and specific modes. I make normative assumptions about how cordon pricing, congestion relief strategies, and transit investments may alter travel times in different locations and at different times of day. These are informed by observed travel speed reductions in previous implementations of cordon pricing in London, Stockholm, and Singapore. For reference, in London cordon pricing led to a 30 percent increase in average travel speed, in Stockholm traffic delays reduced between 30 to 50 percent, and in downtown Singapore vehicle speed increased by 30 percent (Tri-State Transportation Council, 2018). In the summary table of each alternative below, "auto" applies to the drive alone, shared ride, and ridesource modes.

		Alternatives	
		Scenario 1: Seattle-Centric Investment	Scenario 2: Regional Transit Expansion
Level-of-Service Adjustments Relative to Current Conditions	Auto Travel Cost	+$5	+$5
	Auto Travel Time in Center City (peak)	−30%	−15%
	Transit Travel Time in Center City (peak)	−30%	−45%
	Auto Travel Time in Center City (non-peak)	−5%	−5%
	Transit Travel Time in Center City (non-peak)	−5%	−25%
	Auto Travel Time in Seattle (peak)	−5%	-
	Transit Travel Time in Seattle (peak)	−5%	−45%
	Auto Travel Time in Seattle (non-peak)	−5%	-
	Transit Travel Time in Seattle (non-peak)	−5%	−25%
	Auto Travel Time in King County (peak)	-	-
	Transit Travel Time in King County (peak)	-	−45%
	Car Travel Time in King County (non-peak)	-	-
	Transit Travel Time in King County (non-peak)	-	−25%

Table 18: Summary of Model Level-of-Service Adjustments

It is implicit that both scenarios will reduce travel times relative to current conditions based on previous cordon pricing traffic impacts in London, Stockholm, and Singapore. Scenario 1: Seattle-Centric Investment provides higher travel time savings for private automobile modes within Center City relative to Scenario 2: Regional Transit Expansion. However, Scenario 2 provides higher travel time savings for transit across the region relative to Scenario 1.

Applying adjustments in level-of-service variables relative to current conditions within the mode choice model produces new mode share estimates. The following sections present the percent change in trips or mode shares relative to current conditions for each scenario.

Scenario 1: Seattle-Centric Investment

The first strategic goal under consideration is congestion mitigation, for which impact is measured by the change in automobile trips at various locations and times of day. The change in trip volumes is estimated by the percent change in aggregate drive alone, shared ride, and ridesource mode share.

Location			Time of Day: Non-peak	AM Peak (6AM – 9AM)	PM Peak (3PM – 6PM)
Location	Work	Center City (Seattle)	-24.0	-28.9	-28.4
		Outer Seattle	-8.1	-11.2	-12.9
		King County	5.4	-3.6	-4.0
	Non-Work	Center City (Seattle)	-9.8	-6.2	-6.9
		Outer Seattle	-0.8	-0.4	-0.4
		King County	-1.7	0.1	0.2

Table 19: Percent Change in Daily Automobile Trips by Time of Day and Location

The models predict that peak hour work trips will be more sensitive to the cordon price than non-peak hour work trips in Center City and Outer Seattle, while the reverse is true in King County. Automobile work trips may increase in King County because travel times improve for driving modes but not for transit; therefore, the cordon price may actually slightly worsen regional congestion under this scenario. Non-work trips are less sensitive than work-trips to the price increase, and non-peak non-work trips are less sensitive to the cordon price than peak hour trips.

The model predicts a 12% trip reduction, or 84,000 trips. The model predicts that there will be 667,000 daily automobile trips into Center City. Based on the PSRC trip tables, 88% of trips in the cordon zone are generated from outside the cordon zone itself, so we expect that 88% of the 667,000 trips will pay the $5 fee. It is estimated that the cordon fee will generate $1,071,202,000 in revenue per year.

The second and third strategic goals, expanded multimodal options and equity, are evaluated simultaneously by estimating how travelers' mode choices change at different income and vehicle ownership levels.

			Vehicle Ownership								
			No Vehicles			Vehicle-Constrained			Vehicle-Abundant		
			Auto	TNC	Transit	Auto	TNC	Transit	Auto	TNC	Transit
Income Percentile	Work	$< 25^{th}$	-20.9	-22.3	0.2	-15.2	-26.2	7.5	-7.0	-16.2	5.6
		$< 50^{th}$	-32.5	-36.7	0.0	-5.4	-14.7	4.9	-9.9	-21.6	7.6
		$< 75^{th}$	-28.6	-35.6	0.7	-15.6	-28.4	4.8	-8.7	-24.0	7.4
		$\geq 75^{th}$	-16.7	-35.1	0.4	-16.0	-26.7	3.7	-8.5	-24.1	6.7
	Non-Work	$< 25^{th}$	-20.0	-30.6	0.4	-7.2	-13.3	6.7	-1.1	-5.3	2.9
		$< 50^{th}$	-16.1	-17.9	0.7	-3.1	-4.0	2.0	-2.2	-7.8	1.3
		$< 75^{th}$	-12.5	-23.9	0.9	-4.7	-8.9	9.0	-1.7	-5.0	2.1
		$\geq 75^{th}$	-14.4	-32.0	-0.1	-4.1	-14.8	1.8	-1.2	-7.0	0.3

Table 20: Percent Change in TNC, Personal Automobile, and Transit Mode Shares (%) by Income Percentile and Vehicle Ownership

Scenario 1 reduces the use of car-based modes, but with only modest increases in transit use. This may be because people who shift are more likely to shift to active modes like walking and biking in the absence of transit improvement. The model predicts that transit use increases the most among those from vehicle-constrained and vehicle-abundant households, likely because travelers from zero-vehicle households already have high levels of transit use. Additionally, the model predicts that higher income travelers increase their use of transit less than lower income travelers. This is likely because the cordon price is more cost-prohibitive for lower-income travelers. Scenario 1 increases transit use most among those with already high transportation need, but by making driving even less affordable rather than by making transit more accessible. TNC use decreases the most for those in zero- and low-vehicle households, and the most for higher-income travelers. Therefore, the shared mobility equity impacts of Scenario 1 are mixed, as those who are already disadvantaged by lack of vehicle access reduce their TNC use the most, whereas those who are disadvantaged in terms of low income are expected to reduce their TNC use the least.

Segmenting populations by varying housing and transportation affordability also provides a look into both multimodal behavior and equity.

			Mode Share			
			Auto	TNC	Transit	Active
Population-weighted Percentile of Housing + Transportation Affordability (<25th is least affordable)	Work	< 25th	-5.1	-17.2	16.9	4.8
		< 50th	-8.5	-22.4	17.9	6.9
		< 75th	-7.4	-22.1	14.3	3.8
		≥ 75th	-14.4	-30.9	12.6	4.5
	Non-Work	< 25th	0.0	0.5	-0.1	-0.3
		< 50th	-0.1	-1.5	-0.2	1.3
		< 75th	-0.6	-7.3	0.6	3.7
		≥ 75th	-3.5	-13.7	1.9	6.7

Table 21: Percent Change in Travel Mode Shares (%) by Housing and Transportation Costs as Percent of Income for the Average Census Tract Household

Those who reside in the least affordable neighborhoods reduce their automobile use and TNC use the least. Those from the least affordable neighborhoods increase their transit use and active travel for work trips, but reduce their transit use and active travel for non-work trips. This is because those in the least affordable neighborhoods have high automobile mode share and low transit mode share, so reductions in automobile use imply small percent changes and increases in transit mode share imply high percent changes respectively. Scenario 1 increases multimodality, particularly for work trips and towards transit use, but it reduces TNC and shared mobility use, especially among those who currently use it the most.

The final strategic goal under consideration, greenhouse gas emissions reduction, can be evaluated using mode share impacts for different segments of average census tract emissions.

			Mode Share			
			Auto	TNC	Transit	Active
Population-weighted Percentile of Annual Greenhouse Gas Emissions (<25th percentile is least emitting)	Work	< 25th	-19.6	-33.1	11.5	4.3
		< 50th	-11.2	-19.4	12.4	5.0
		< 75th	-6.4	-12.2	10.4	3.3
		≥ 75th	-5.0	-15.3	14.8	4.2
	Non-Work	< 25th	-7.9	-21.5	2.5	6.7
		< 50th	-1.3	-4.2	1.1	3.0
		< 75th	-0.6	-2.8	0.9	1.3
		≥ 75th	0.1	0.1	-1.2	0.0

Table 22: Percent Change in Travel Mode Shares (%) by Annual Greenhouse Gas Emissions for Average Census Tract Household

Scenario 1 generally reduces automobile use and increases transit use, especially for work trips, but the most dramatic improvements occur amongst travelers who reside in the parts of the region that are already the lowest-emitting. This is likely because these areas already have robust transit service, so these travelers are most likely to be willing to shift trips to transit under the implementation of a cordon price. Therefore, this scenario does reduce transportation sector greenhouse gas emissions relative to current conditions, but these reductions are concentrated in neighborhoods which are already relatively low carbon.

Scenario 2: Regional Transit Expansion

Scenario 2 is evaluated relative to current conditions under the same framework as Scenario 1. The first strategic goal under consideration is traffic congestion mitigation, for which improvement is measured by the percent change in automobile trip volumes.

			Time of Day		
			Non-peak	AM Peak (6AM – 9AM)	PM Peak (3PM – 6PM)
Location	Work	Center City (Seattle)	-26.2	-32.1	-31.6
		Outer Seattle	-10.0	-16.0	-17.6
		King County	4.9	-7.5	-7.4
	Non-Work	Center City (Seattle)	-9.9	-8.4	-10.2
		Outer Seattle	-0.9	-0.7	-0.8
		King County	-1.7	0.0	0.0

Table 23: Percent Change in Daily Automobile Trips by Time of Day and Location

Trips in Center City are predicted to decrease significantly, particularly during the AM and PM peaks. Automobile trips in Outer Seattle and King County generally decrease, except in King County during the non-peak period. The reduction in automobile work trips in Outer Seattle and King County is likely driven by improved transit service that enables travelers throughout the region to shift away from driving modes.

Scenario 2 is expected to reduce vehicle traffic in Center City by 13%, which similar to the reduction predicted under Scenario 1. This is achieved even though travel speeds in Center City improve less, because more of the traffic reduction is due to mode shifts by travelers outside Seattle. This suggests higher VMT reductions in Scenario 2 relative to Scenario 1 because the eliminated driving trips are longer under Scenario 2.

With an expected 656,000 daily trips into or within the cordon zone, Scenario 2 will generate $1,053,536,000 in annual revenue.

The second and third strategic goals, expanded multimodal options and equity, are evaluated simultaneously by examining how travelers' mode choices change by different income and vehicle ownership levels.

			Vehicle Ownership								
			No Vehicles			Vehicle-Constrained			Vehicle-Abundant		
			Auto	TNC	Transit	Auto	TNC	Transit	Auto	TNC	Transit
Income Percentile	Work	$< 25^{th}$	-24.4	-24.2	5.9	-17.9	-28.6	17.7	-9.6	-17.8	25.7
		$< 50^{th}$	-36.8	-39.7	5.6	-9.5	-21.5	17.0	-13.0	-24.7	26.5
		$< 75^{th}$	-33.4	-37.9	6.1	-19.8	-31.5	18.5	-11.4	-26.6	27.1
		$\geq 75^{th}$	-21.4	-38.1	5.6	-19.8	-29.7	18.5	-10.8	-26.6	28.3
	Non-Work	$< 25^{th}$	-23.8	-32.7	0.8	-7.6	-14.2	8.2	-1.4	-5.8	5.1
		$< 50^{th}$	-18.4	-20.1	1.3	-3.3	-4.3	2.7	-2.6	-9.1	4.0
		$< 75^{th}$	-15.1	-28.3	1.8	-5.2	-9.5	11.0	-2.0	-7.2	5.2
		$\geq 75^{th}$	-19.8	-34.4	0.9	-4.8	-16.0	4.8	-1.4	-8.9	4.2

Table 24: Percent Change in TNC, Personal Automobile, and Transit Mode Shares (%) by Income Percentile and Vehicle Ownership

Transit use increases the most for travelers from vehicle-abundant households, while TNC use decreases the most for travelers from vehicle-constrained households. All households reduce their automobile use. For travelers from vehicle-abundant and vehicle-constrained households, those from lower income households experience lower shifts away from automobile use than those from higher income households. This has positive equity implications for both dimensions of transportation need, vehicle access and income because there is less evidence that low-income or high-need travelers are disproportionately shifted away from driving due to the cordon fee. For multimodality it means that choice riders are experiencing service improvements that incentivize them to use transit more.

Population segments of varying housing and transportation affordability can also reveal the interplay between multimodal behavior and equity.

			Mode Share			
			Auto	TNC	Transit	Active
Population-weighted Percentile of Housing + Transportation Affordability ($<25^{th}$ is least affordable)	Work	$< 25^{th}$	-7.1	-19.9	24.4	3.2
		$< 50^{th}$	-11.0	-25.6	24.9	4.6
		$< 75^{th}$	-9.9	-25.0	20.3	2.4
		$\geq 75^{th}$	-22.0	-33.7	17.3	3.1
	Non-Work	$< 25^{th}$	-0.2	0.2	3.4	0.3
		$< 50^{th}$	-0.3	-4.3	2.2	1.1
		$< 75^{th}$	-1.1	-14.8	2.6	2.5
		$\geq 75^{th}$	-9.5	-19.7	3.7	6.2

Table 25: Percent Change in Travel Mode Shares (%) by Housing and Transportation Costs as Percent of Income for the Average Census Tract Household

Those who live in the least affordable areas increase their transit use the most and decrease their TNC use the least. Where affordability is highest and transit use is already high, automobile use decreases the most proportionally. Therefore, the model predicts that the regional transit expansion under Scenario 2 will provide benefit to both people of highest and lowest multimodal transportation need, but especially those with high need.

The final strategic goal under consideration, greenhouse gas emissions reduction, can be evaluated using mode share impacts for different spatial segments of average census tract emissions.

			Mode Share			
			Auto	TNC	Transit	Active
Population-weighted Percentile of Annual Greenhouse Gas Emissions (<25th percentile is least emitting)	Work	< 25th	-23.2	-36.3	15.5	3.3
		< 50th	-16.3	-27.8	20.4	3.3
		< 75th	-9.9	-19.9	19.2	1.7
		≥ 75th	-7.5	-22.3	25.3	2.4
	Non-Work	< 25th	-8.9	-23.7	4.3	7.1
		< 50th	-1.7	-6.2	2.9	3.3
		< 75th	-0.8	-3.8	2.6	1.3
		≥ 75th	0.0	0.0	1.0	-0.1

Table 26: Percent Change in Travel Mode Shares (%) by Annual Greenhouse Gas Emissions for Average Census Tract Household

The model predicts that transit use of households from the highest emitting neighborhoods will increase more than that of households from lower emitting neighborhoods, while reductions in automobile use and TNC use will still be concentrated amongst travelers from already low-emitting neighborhoods. Scenario 2, as compared to current conditions and Scenario 1, is expected to produce the greatest reductions in greenhouse gas emissions regionally because it induces the most significant mode shifts to transit and active modes.

EVALUATING TRADE-OFFS

Summarizing the outcomes of each alternative relative to current conditions by strategic goal enables us to compare the relative merits and trade-offs between different implementations of cordon pricing. The strategic goals are also organized by local (Seattle) strategic goals and regional (King County and Sound Transit) strategic goals.

First, the project outcomes of both scenarios suggest that cordon pricing will be effective at reducing congestion and emissions in Center City. Yet this finding alone is not sufficient to motivate its implementation, as it is accompanied by other community concerns such as equity and access. Therefore, we look to impacts along other strategic goals in order to determine whether cordon pricing in Center City Seattle is in alignment with the entire suite of programmatic objectives earlier defined.

Strategic Goal			Alternatives: Current Conditions	Alternatives: Scenario 1: Seattle-Centric Investment	Alternatives: Scenario 2: Regional Transit Expansion
	Local	Congestion Relief	750,000 daily vehicular trips in/to Center City	12% vehicular trip reduction in Center City	13% vehicular trip reduction in Center City
	Local	Equity and Multimodality	Low-income and zero-vehicle travelers exhibit highest transit ridership, while low-affordability areas exhibit automobile dependence	Low-income travelers increase transit use due to relative cost increase of driving. Shared mobility/TNC use decreases, especially for those who already lack vehicle access	Both choice riders and captive riders increase transit use: those from low affordability neighborhoods increase transit use the most. TNC use decreases the most amongst choice transit riders
	Local	Emissions Reductions	25% of residents reside in tracts with low-carbon travel behaviors like low automobile mode share and high transit and active mode share	5% Greenhouse gas emissions reductions due to mode shifts from driving in highest-emitting neighborhoods	7.5% Greenhouse gas emissions reductions due to mode shifts from driving in highest-emitting neighborhoods
	Regional	Transit Access and Expansion	Transit mode share in Greater King County ranges from 22% for work trips to 4% for non-work trips	Transit mode share in Greater King County increases 14% for work trips but decreases 1% for non-work trips	Transit mode share in Greater King County increases 25% for work trips and increases 1% for non-work trips

Table 27: Summary of Cordon Pricing Alternatives Compared to Current Conditions

Although the models predict similar overall automobile trip reductions in Center City under both Scenario 1 and Scenario 2, equity implications vary. Under Scenario 1, in absence of regional transit expansion but significantly improved mobility within Seattle, mode shifts away from driving are largely induced by the relative unaffordability of driving once a cordon fee has been imposed. This is evidenced by a disproportional shift to transit exhibited by low-income travelers and travelers without personal vehicle access, two groups that are most likely to have highest need for multimodal transportation access. Therefore, even though multimodality increases under this scenario it is largely driven by cost disincentives, which does not truly imply enhanced multimodal travel options relative to current conditions. However, under Scenario 2 both choice and captive riders increase their transit use, which implies that regional transit expansion could induce vehicular trip reductions that are more fairly distributed along populations of varying transportation advantage. This implies that Scenario 2 enhances both equity goals and multimodal travel options more than Scenario 1 does, as well as relative to current conditions.

For both alternatives, greenhouse gas emissions reductions are induced by the introduction of cordon pricing across the region due to mode shift away from automobile-based modes including driving alone, shared ride, and ridesourcing. However, reductions associated with either alternative are concentrated in households that already reside in low-emitting areas, likely due to the availability of transit options and dense, walkable environments. Still, Scenario 2 produces more mode shifts away from automobile in the neighborhoods where emissions reductions have the highest impact and trips are the longest than Scenario 1 does - 7.5 percent as compared to 5 percent reduction in greenhouse gas emissions due to automobile travel. Therefore, although both scenarios advance greenhouse gas emissions reductions strategic goals, Scenario 2 is more effective than Scenario 1.

Finally, regional transit access is bolstered by increases in regional transit ridership. Although transit ridership in and into Seattle is high, there are still service gaps and low ridership areas in Greater King County. Both scenarios increase transit mode share for work trips as compared to current conditions, but Scenario 1 actually decreases transit ridership for non-work trips while Scenario 2 increases transit ridership for non-work trips. This is likely because without investment in regional transit service in Scenario 1, the improved traffic congestion in Center City Seattle and Outer Seattle actually attract more vehicle trips even though there is a new fee on such trips. Conversely, Scenario 2 increases transit ridership. Therefore, increased transit investment in the region best improves transit access and increases transit mode share.

SUMMARY

Both Scenario 1: Seattle-Center Investment and Scenario 2: Regional Transit Expansion offer congestion mitigation and greenhouse gas emissions reductions, but Scenario 2 best advances strategic goals related to transportation equity, multimodal travel options and expanded regional transit supply. Cordon pricing will mitigate several of the transportation and social challenges in Seattle, and can raise over $1 billion in revenue annually. Investment of that revenue in regional transit service produces outcomes that advance congestion relief, equity, multimodal travel options and climate goals in Seattle as well as outcomes that enhance regional transit service for Sound Transit and King County Metro. Cordon pricing can be an instrument for charging drivers for the negative externalities they produce and the resulting revenue can be redistributed to enhance transportation equity in the region. Ultimately, the revenue will provide benefits to both those who pay (reduced travel times in Center City) and those who are disadvantaged (improve transit access and service). Based on my findings, diverse populations and policy goals are best served when revenue is invested in transit service expansion throughout the region.

Chapter 6: Conclusion

Challenges and Opportunities

Economic and social trends drive the confluence of transportation issues in the Greater Seattle region. At the same time, worsening traffic congestion both on highways and city streets stifle economic growth and threatening quality of life. Transportation funding is becoming increasingly scarce as the revenue from the gas tax declines. A housing affordability crisis prevents many people from living near work, recreation, and other opportunities that make their lives meaningful. Finally, transportation sector greenhouse gas emissions are the single largest factor standing between Seattle and its zero-emissions goals.

State, regional, and local agencies have adopted various strategies and plans in order to lay the groundwork towards overcoming these issues, but gaps remain. Washington State Department of Transportation (WSDOT) has begun operating managed lanes or dynamically-priced high occupancy toll lanes on several miles of highway throughout the region to improve traffic speed and travel time reliability. However, cities in the Seattle region continue to climb in the nationwide ranks for cities with the worst traffic congestion. Furthermore, with the coming "Seattle Squeeze," Center City Seattle anticipates perhaps the worst traffic congestion its history in the next 5 years due to numerous planned lane closures.

The Washington state legislature approved gas tax increases of roughly 7 and 4 cents per gallon in 2015 and 2016, respectively, while electric vehicle drivers must pay $150 a year for vehicle registration, nearly $100 more than owners of conventional vehicles do. The state also concluded a Road Usage Charge pilot in January 2019 to investigate whether a road usage charge could serve as a viable long-term funding source in lieu of the gas tax. These initiatives demonstrate that policymakers in the state are searching for new sustainable transportation funding sources, but it is unclear how these statewide funding streams might translate to implications for transportation funding regionally and locally.

The Seattle area spends more per capita on transit than any other region in the country, and the area is one of few American metropolitans where transit ridership is increasing. King County Metro has published a long-range plan with ambitious expansion goals. In 2016, voters passed Sound Transit 3, a $53.8 billion ballot measure to add 62 additional miles of light rail throughout the region (Gutman, 2017). However, King County still calls out significant anticipated funding gaps in their plans, with a $4 billion shortfall by 2025 and a $7.8 billion shortfall by 2040. Other multimodal initiatives acknowledge the importance of incorporating emerging transportation modes and services; Seattle Department of Transportation (SDOT) published a New Mobility Playbook that outlines strategies for public-private collaboration. However, numerous city-proposed legislation to regulate TNCs in the last year have been met with strong opposition by those companies.

Seattle has a strong commitment to social and racial justice, and instituted a Transportation Equity Program in 2017 that is funded by the Seattle Transportation Benefit District. The program has enabled SDOT, the Seattle Housing Authority, and King County Metro to provide unlimited ORCA cards to 1,500 low-income Seattle residents and other equity-oriented programs (Chiachiere, 2019). However, the tax package that created the Transportation Benefit District is due to expire in 2020, and the last time King County attempted to pass a similar Transportation Benefit District the measure failed at the ballot box (Johnson, 2019). The aforementioned transit and equity programs are critical components of Seattle's, King County's and Sound Transit's strategic visions, but their successes hinge upon uncertain funding conditions.

To address greenhouse gas emissions, Seattle renewed commitment to its climate action plan in 2018. In it, the first near-term climate action priority for the transportation sector is congestion pricing. It announces that Seattle "will develop and release a strategy to address congestion and transportation emissions through pricing, coupled with investments in expanded transit and electrification in underserved communities" (City of Seattle, 2018).

Cordon pricing is receiving attention in numerous U.S. cities, and none have yet found an approach that survived legislative or referendum processes. The transportation sector needs to prove to statewide, regional, and local policymakers and constituents that congestion pricing would be worth the dramatic shift in how people pay for and perceive transportation options. Furthermore, policymakers and the transportation sector will need to iron out details like revenue allocation and exemptions and pricing structures that balance a variety of sometimes contradictory strategic goals. Despite the complex process, the convergence of priority problems, viable policy solutions, and political interest presents a rare window of opportunity to translate policy ideas into action. Therefore, Seattle should evaluate whether congestion pricing with a geographically and programmatically targeted allocation of revenue can gain traction in for the city and the region. Policymakers desire a cordon pricing strategy that can generate positive impacts beyond congestion and emissions; with the right strategies in place, this could be an opportunity for Seattle to address longstanding equity challenges and for regional transit providers to secure sustainable new funding sources. This thesis seeks to provide an empirical argument for cordon pricing and the use of its revenue.

DEVELOPING THE CASE FOR CORDON PRICING IN SEATTLE

Many challenges accompany the task of composing a policy that is unified across numerous strategic goals. Seattle's early interest in congestion pricing has sparked a lively public discourse. Many opinions have already weighed in on the prospect of downtown congestion pricing, with a mix of usual and unexpected voices. A Washington state legislator introduced a new bill in early 2019 that would prevent local jurisdictions from implementing congestion pricing (Robertson, 2019). On the other hand, both TNCs and transportation advocates have spoken in favor of the idea, though perhaps with differing motivations. TNCs prefer congestion pricing as an alternative to proposals to levy surcharges only on TNC trips (Nickelsburg, 2019). In general, transportation advocates support the further investigation of congestion pricing because it leverages economic principles that demonstrate to drivers the true cost of their choice, including the external costs of congestion, pollution, and crashes.

A complex and nuanced policy debate is sure to come if the city continues to pursue cordon pricing as a policy solution. The PSRC's 2010 tolling study identified barriers that Seattle and the region will have to address in order to make the case for congestion pricing. Fairness and how the revenue is spent will be prominent issue. However, evaluating fairness is complicated because travelers have varying preferences and attributes and because measuring transportation need and equity is nuanced. Distributing road pricing revenue could require an adjustment or overhaul of the entire regional transportation funding landscape, which would spark further equity discussions. Finally, the current alternative options to driving are limited, so some people may have no choice but to pay the tolls or congestion prices.

These thorny revenue questions around congestion pricing present both a challenge and an opportunity when we elevate the discussion to a regionwide perspective. Currently, Sound Transit and King County Metro source 66% and 52% of their revenue from sales taxes, respectively (Sound Transit, 2018; Metro Transit, 2018). The sales tax is a common fundraising mechanism for local transit programs across the country because of its political feasibility and ability to generate large amounts of revenue, but from a tax policy perspective it has drawbacks. The sales tax is generally considered regressive because people with the lowest incomes pay the highest proportion of their income in sales taxes, even when exemptions are in place for essential goods. This is a serious concern because Washington state is has the most regressive tax structure in the nation and Seattle has the most regressive tax structure in the state (Institute of Taxation and Economic Policy, 2018; Caruchet, 2018). The sales tax is in not transparent when used to fund transit, because there is only weak tax-benefit linkage between those who pay the sales tax and the benefits received from transit. The sales tax is also difficult for taxpayers to account for, which obscures the true cost of funding transit programs from taxpayers. One advantage of the sales tax is that it collects revenue from people who travel from outside of the jurisdiction; traffic congestion and its negative externalities are mostly produced by drivers who come into or pass through the region, and the sales tax can recoup some of the cost of hosting these visitors in a way that a property tax cannot. Yet, a cordon toll achieves this effect as well, by charging every person who drives into Center City regardless of where they live or came from. And while the cordon toll is arguably regressive as well, with relatively higher cost to low-income than high-income travelers, it is more straightforward and transparent to build in exemptions or reduced fees that can ameliorate its regressivity.

DEMONSTRATING THE BENEFITS

Whether or not cordon pricing will be possible in Seattle depends up several political factors. The state can play a large role in either advancing or blocking cordon pricing proposals, and the 2019 legislative session will produce an early indication of the statewide political appetite for cordon pricing. Seattle voters will need to decide whether or not cordon pricing in Center City is right for them as well. Transportation advocacy groups, city and regional agencies, and elected officials can communicate the impacts and benefits that all the different types of travelers might experience, from drivers who will experience faster or more reliable travel times to transit users who will experience better quality or more accessible trips. This thesis evaluates the extent to which both the regional transportation system and individual travelers can benefit under the right congestion pricing formulation. These findings can motivate regional partners to join together to unlock the benefits of coordination.

First, my findings suggest that cordon pricing in Center City will reduce traffic congestion within the cordon, with an average of 12 to 13 percent reduction in trips into, out of, and through Center City, and with even higher reductions during peak hours. Cordon pricing will generate around $1 billion in annual total revenue. King County Metro and Sound Transit each bring in between $1.7 to $2 billion in annual revenue through existing funding mechanisms; the comparative revenue potential of cordon pricing could go a long way in reducing these agencies' reliance on sales tax revenue and towards financing transit system expansions.

Second, two scenarios of revenue use are compared: one in which most revenue is concentrated on transit and roadway improvements in Seattle and one in which revenue is spread across the region to expand transit service. My findings suggest that the investment scenario that emphasizes regional transit investment produces better outcomes across multiple City of Seattle and regional strategic goals. For instance, under the Seattle-centric scenario most of the mode shift to transit is by low-income and low-vehicle travelers, likely only reducing the quality of their trips, whereas under the regional transit expansion scenario the distribution of those who shift to transit is much more evenly dispersed, implying that better quality transit drives the shifts. This is telling for both strategic goals towards equity and increased multimodal travel options. Both strategies increase multimodal behavior, but one does so by imposing a high cost on driving without improving transit, so only those who cannot afford to drive do not. The other expands multimodal options for many more travelers, so though the cost of driving increases, the benefit and attractiveness of transit does too. The evidence also suggests that regional transit investment would induce more greenhouse gas emissions reductions than Seattle-centric investment, particularly amongst households that are currently the highest emitting. This is primarily because households that emit the most are those that are located in areas with little to no transit service and which tend to travel the most due to sprawling urban forms. By introducing expanded transit services into these neighborhoods, even small mode shifts from driving to transit add up.

Based on the suite of policy criteria that I selected based on the regional policy context, there is strong justification for Seattle, King County Metro, and Sound Transit to coordinate a congestion pricing proposal, campaign, and implementation. Together they can devise a plan for how revenue will be spent that will be appealing to voters and drum up unilateral support from elected leadership within Seattle and the region.

IMPLICATIONS FOR FUTURE RESEARCH AND POLICY DEBATE

My research leads into several new policy and research questions for the Greater Seattle region. The first emerging research opportunity concerns the specific programs that revenue from cordon pricing could fund to best advance equity, multimodal, and climate goals. The second emerging research opportunity concerns the suite of discounts, caps, and exemptions that could be built into a cordon pricing scheme to best advance equity, multimodal, and climate goals.

If Seattle region invests cordon pricing revenue towards transit system expansion and improvement, decision makers should analyze the comparative benefits of transit-related programs and services. There are opportunities to fund the capital and operating costs associated with increased bus or light rail service along existing routes or strategically selected new ones, express transit routes, and commuter routes. The revenue could also be used to expand the zero-emission bus fleet and advance equity. In 2017, King County identified which areas in the county faced the greatest exposure to transportation sector emissions, poor air quality, and social exclusion, and identified where zero-emission bus routes would create the most positive equity impacts (Metro Transit, 2017). Other equity-related programs could be funded by the revenue, such as subsidized or free transit passes or student transit passes. Other programs to be funded could be those that advance shared mobility and increase emerging multimodal travel options. For instance, Pierce County to the south of King County is piloting a partnership with Lyft to provide first and last mile connectivity to those who typically have no or limited access to transit (Pierce Transit, 2019). Some revenue could even be spent on expanding public-private bikeshare or carshare programs, which could provide increased options to communities which currently have low access to shared mobility due to unfavorable markets for shared mobility providers. Future research could contribute to understanding the benefits and drawbacks of funding each of these types of programs using new cordon pricing revenue. A structured approach that uses empirical methods to compare these different programs would be instrumental in the ultimate policy design. These details that can make or break a cordon pricing proposal, so more research can provide an evidence-based case for a particular portfolio of investments using cordon pricing revenue.

The details of cordon pricing implementation also present some new research questions. For instance, Seattle may want to consider providing discounts to certain types of travelers, such as low-income travelers, disabled travelers, small business owners or employees, high-occupancy vehicles, or alternative fuel vehicle drivers. When the region's Transportation Futures Task Force conducted roundtable discussions to gather feedback about how transportation funding mechanisms might affect target populations, there was broad consensus that any funding mechanism, including congestion pricing, should provide fee reductions or complete exemptions for people with low incomes (Futures Task Force, 2015). Analysis that accounts for the different travel behaviors of these different populations in determining the congestion, emissions, and equity outcomes under various fee structures will be instrumental in enabling policymakers to craft a data-driven and equitable strategy.

Finally, we need to understand how cordon pricing will shape long-term regional outcomes. Key drivers of transportation behavior such as residential location, employment location, and vehicle ownership could change in response to cordon pricing in Center City Seattle, which in turn could moderate the long-term impact that the policy would have on congestion, emissions, and transportation revenue. Research also needs to address how cordon pricing will interact with land use, housing, and regional growth. This too could alter the expected congestion, emissions, and revenue outcomes of a cordon pricing scheme if economic development and real estate development shifts throughout the region as a result of cordon pricing. Policymakers and planners will be concerned with how these patterns might impact the landscape of housing and transportation affordability in the region and may wish to deploy tools such as transit-oriented development and affordable housing initiatives to shape sustainable and equitable development patterns.

This thesis begins the work of building a case for a cordon pricing proposal in Seattle that aligns the strategic goals of the City of Seattle and regional partners King County Metro and Sound Transit. The empirical findings can inform the early principles behind a proposal, such as which investment strategies benefit the most people at once. Agencies and policymakers can use these initial findings to guide budget negotiations and programmatic investments and build consensus around policy and proposal details that deliver outcomes that advance diverse goals and serve diverse needs.

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Vita

Amy Zhang Fong was raised at the base of the Santa Monica Mountains in Newbury Park, California. She realized her fascination with transportation systems when she moved to the San Francisco Bay Area and began riding trains and buses to explore her new home. Her passion for public service led her to pursue graduate studies at the confluence of transportation engineering, governance, and policy. Amy enjoys practicing yoga, cooking vegan meals, volunteering for causes related to conservation and women's empowerment, and being outdoors.

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