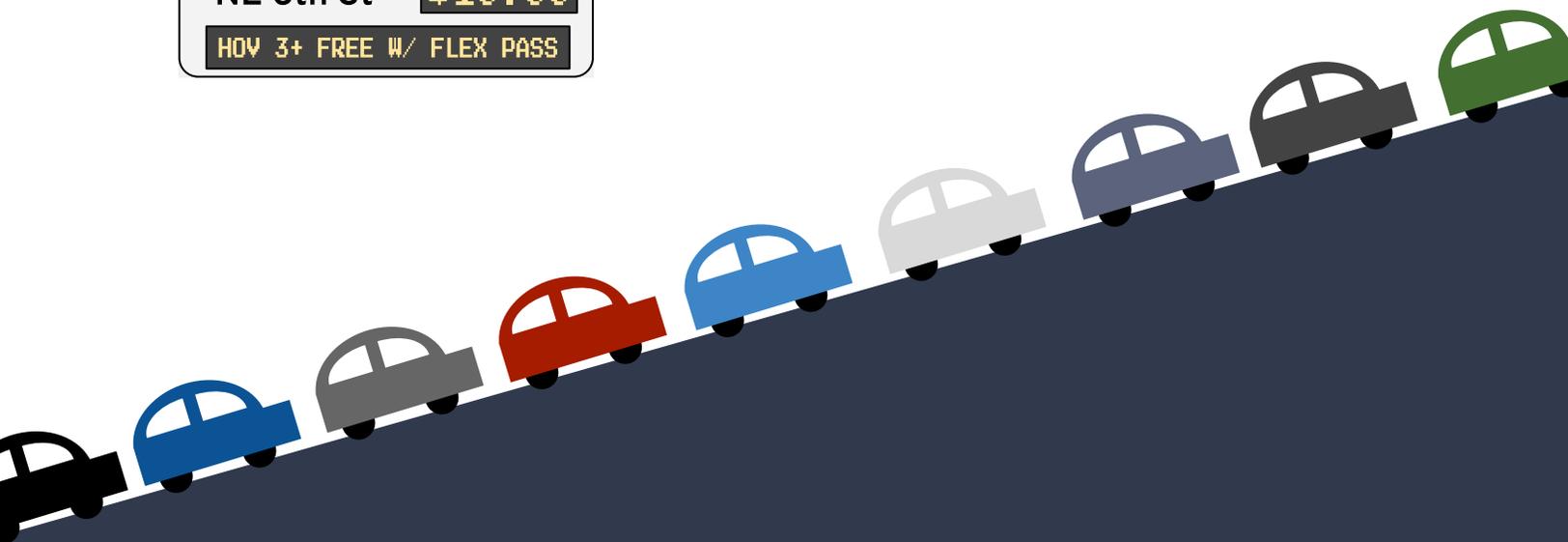


I-405 Express Toll Lanes

Usage, Benefits, and Equity

EXPRESS TOLL LANES 	
NE 128th St	\$10.00
NE 85th St	\$10.00
NE 6th St	\$10.00
HOV 3+ FREE W/ FLEX PASS	



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Table of Contents

Executive Summary	vii
Usage Patterns	vii
Overall Facility Benefits.....	vii
Distribution of Facility Benefits.....	viii
Policy Analysis	viii
Chapter 1: Introduction	1
Background.....	1
Research Questions.....	2
Analysis Factors.....	2
Data	2
2018 WSDOT Survey.....	3
Income Distribution	3
Time Savings and Reliability	3
Chapter 2: Usage Patterns.....	6
Usage by Geography	6
Income and Race Reference Maps	6
Number of Trips	7
Average Toll and Trip Distance	7
Usage by Income	8
Regional Income Distribution	8
Number of Trips	9
Paying Versus Carpooling Users	10
Time of Day and Direction	10
Toll Paid	12
Frequency of Use	12
Usage Differences Between Paying and Carpooling Users	14
Time of Day	15
Frequency of Use	15
Usage by Route	16
Overall Volume	18
Toll Cap	19

Peak Use	20
Chapter 3: Overall Facility Benefits	21
Modeling HOT Lane Usage	21
Value of time (VOT) and Estimated Time Savings	21
Value of Reliability (VOR) and Estimated Reliability	22
Price Elasticity	23
Overall Findings	24
Differences by Time of Day	24
Aggregate Benefits	25
Chapter 4: Distribution of Facility Benefits.....	27
Geographic Distribution	27
Time and Reliability Savings	27
Net Benefit Per Household and Per Dollar	28
Income Distribution	28
Per Household	29
Per Trip	29
Distribution Among Lower-Income Users	32
Frequency of Use Distribution	33
Route Distribution	34
Conclusions	35
Chapter 5: Policy Analysis	37
Raising the Minimum Toll	37
Methodology	37
Facility-Wide Change in the Minimum Toll	37
Selective Change in the Minimum Toll	38
Raising the Maximum Toll	38
Methodology	39
Moderate Price Sensitivity	39
Higher Price Sensitivity	40
Appendix A: Data Statistics and Quality	41
Trip Data	41
Census Data	41
Appendix B: Income Methodology.....	42

Fitting Distributions to Income Histograms	42
Estimating How Quantities of Interest Vary by Income	42
Bad Assumption: Usage Is Independent of Income, Given a Neighborhood	42
Better Assumption: Usage Is Independent of a Neighborhood's Income, Given Neighborhood Location and Individual Income	43
Appendix C: Modeling HOT Usage	44

Figures

Figure 1.1. Income frequency	4
Figure 1.2. Time savings and reliability survey responses	4
Figure 1.3. Time savings and reliability survey responses across incomes.....	5
Figure 2.1. Household income	6
Figure 2.2. Percentage of white households	6
Figure 2.3. Trips per household	7
Figure 2.4. Trips per user	7
Figure 2.5. Average toll per trip.....	8
Figure 2.6. Average trip length	8
Figure 2.7. Trips per household, by income	9
Figure 2.8. Median income of carpoolers versus paying customers.....	10
Figure 2.9. Median income by peak or off-peak facility use.....	10
Figure 2.10. Median income by direction and time of day of use	11
Figure 2.11. Median income by toll paid, rounded up to the nearest dollar.....	12
Figure 2.12. Median income for paying users by frequency of use in 2018	13
Figure 2.13. Median income for paying users by county and by frequency of use in 2018	14
Figure 2.14. Percentage of trips which are HOV by direction and time of day	15
Figure 2.15. Fraction of trips made by paying (SOV) and carpool (HOV) users, by frequency of use	16
Figure 2.16. Facility map.....	17
Figure 2.17. Trip volume by route and time of day	18
Figure 2.18. Fraction of trips charged \$10.00, by route, colored by facility section (one or two lanes).....	19
Figure 2.19. Fraction of trips made during peak period (southbound 5:00 – 9:00 a.m., northbound 3:00 – 7:00 p.m.) by route	20
Figure 3.1. Actual versus estimated time savings, in minutes. Plot margins show marginal densities.....	22
Figure 3.2. Time savings and reliability estimates in 15-minute increments for full- corridor trips in each direction.....	23
Figure 3.3. VOT, VOR, and elasticity estimates by time of day and direction.....	25
Figure 4.1. Time savings per trip, in minutes	27
Figure 4.2. Reliability savings per trip, in minutes	27
Figure 4.3. Highest and lowest quintiles of net benefits per household.....	28
Figure 4.4. Highest and lowest quintiles of net benefits per dollar spent.....	28
Figure 4.5. Net benefit per household by income.....	29

Figure 4.6. Net benefit per trip by income	30
Figure 4.7. Net benefit per trip at block group income.....	31
Figure 4.8. Net benefit per trip at overall median income.....	31
Figure 4.9 Share of users with household income below \$35,000 per year, by time of day and direction	32
Figure 4.10. Net benefit per trip by time of day and direction	32
Figure 4.11. Difference from average net benefit per trip for users with a household income in the 20th percentile	33
Figure 4.12 Percentage of trips during peak periods by frequency of use.....	34
Figure 4.13. Net benefit per trip by frequency of use.....	34
Figure 4.14. Net benefit per trip by route and time of day.....	35

Tables

Table 2.1.	Average travel time savings by facility section and direction	11
Table 2.2.	Frequency of use category definitions and summary statistics.....	13
Table 2.3.	Classification of users by SOV and HOV trips made in 2018	14
Table 3.1.	Model estimates for VOT, VOR, and price elasticities, along with 95 percent confidence intervals	24
Table 3.2.	Average and aggregate time savings, reliability, toll, and net benefit	25
Table 5.1.	Estimated impacts of raising the minimum toll	38
Table 5.2.	Estimated impacts of raising the minimum toll	38
Table 5.3.	Estimated impacts of raising the maximum toll, assuming a price elasticity of -0.64	40
Table 5.4.	Estimated impacts of raising the maximum toll, assuming a price elasticity of -1.2	40
Table A.1.	Data quality summary statistics	41

Executive Summary

Using data on each trip taken on the I-405 express toll lanes during operational hours (weekdays 5:00 a.m. – 7:00 p.m.) in 2018; demographic data on census block groups; and lane speed, volume, and travel time data, we studied how the express toll lanes are used, the benefits they provide to the region, and how these benefits are distributed among different groups of noncommercial users.

Usage Patterns¹

The general findings were as follows:

- Higher-income households take more trips on the facility than lower-income households. However, most users of the facility are not high income.
- High-toll payers have lower incomes than low-toll payers.
- Peak users have significantly lower incomes than off-peak users, and morning peak users have slightly lower incomes than afternoon peak users.
- On average, drivers making trips in the south end of the facility have higher incomes than those making trips in the north end, although there is variation by the particular route (start and end point on the high-occupancy toll (HOT) lanes.)
- Single-occupancy vehicles (SOVs) do not have a significantly different incomes than high-occupancy vehicles (HOVs).
- HOV usage is highest northbound in the off-peak, at 40 percent of HOT lane volume. HOV usage is lowest southbound during peak hours, at 30 percent of HOT lane volume. HOV usage is around 35 percent for both northbound peak and southbound off-peak.
- One-time users are almost exclusively SOV, while daily users are around 65 percent SOV.
- In 2018, 48 percent of users used the express lanes only once.²
- Eight percent of accounts used the facility more than 40 times during the year.

Overall Facility Benefits

We modeled drivers' choice to enter the lanes on the basis of information available to them, and so can estimate their average value of time (VOT), value of reliability (VOR),³ and price elasticity.

- The overall VOT is around \$53 per hour, and the overall VOR is around \$26 per hour.
- Reliability is as valuable as time savings in the morning, while time savings are much more valuable than reliability in the afternoon.

¹ All of these results describe aggregate or average outcomes. There is wide variation among different users, as well as considerable day-to-day variation.

² "User" here means an identifiable plate or account. There were 828,983 such users in 2018.

³ Reliability is measured in hours. See the detailed findings for a specific definition.

- Price elasticity is approximately -0.64 , which means that on average, a 10 percent toll increase will lead to a 6.4 percent decrease in volume.
- In aggregate, the facility provided \$50 million in time savings and reliability benefits to paying users, while collecting \$31 million in revenue, for a net benefit of \$19 million. Carpool and transit benefits would need to be added to those benefits to estimate the full facility benefits.

Distribution of Facility Benefits

- Because higher-income households take more trips, they accrue significantly more net benefits in aggregate than lower-income users.
- *Per trip*, however, lower-income drivers benefit more than higher-income drivers.
- This difference is not explained by geography; rather, it appears to be mainly a result of low-income drivers travelling more during peak hours, when the largest time savings are found.
- Income aside, the travel shed around the facility north of SR 522 receives the highest net benefit per household, while the travel shed south of I-90 receives the highest total benefit per dollar spent.
- Drivers who use the facility more frequently gain more net benefit per trip than drivers who use the facility infrequently.
- There is significant variation in net benefit by route. Northbound routes that begin south of Kirkland gain on average, while routes beginning north of Kirkland lose on average. Southbound morning routes that end south of SR 522 and southbound afternoon routes that end in Bellevue gain on average, while other southbound routes lose on average.

Policy Analysis

Without individual-level income data, detailed policy analysis is difficult. We analyzed two relatively simple potential policies and their effects on equity, revenue, and overall volume.

- Raising the minimum toll to \$1.00 would have minimal equity impact, while raising revenue by 9% and decreasing volume by 6 percent.
- Raising the maximum toll could increase revenue if drivers are not too price sensitive. If this were the case, a toll cap of \$15 would be revenue-maximizing. A \$15 toll cap would raise revenue by around 1 percent, decrease volume by less than 1 percent, and have little to no impact on equity.

Chapter 1: Introduction

Background

Increasing motor vehicle usage and traffic congestion are growing concerns in many urban and rural areas. Environmental degradation, petroleum-based fuel usage and its resulting contribution to rising carbon dioxide levels, hours spent sitting in traffic, and the lack of reliability in the time it takes to travel from place to place are only a few of the problems caused by traffic congestion that lead to a lowered quality of life.

Congestion pricing is one of the congestion mitigation solutions that is starting to be used across the globe to help alleviate these problems. A variety of different approaches to congestion pricing exist. Each approach has different strengths and weaknesses. High-occupancy toll (HOT) lanes are designed to improve the efficiency of roadways, given the inability to supply roadway capacity to all of the people who would like to use it during peak periods. When congestion is present, HOT lanes help allocate the available roadway space by providing travelers with a price/performance choice that allows each user to select for each trip they make whether to pay a lower cost but travel a slower and less reliable travel path, or to pay more but experience a faster and more reliable path.

Relatively little work has been done to explore how travelers actually use this approach. Do only high-income households pay for faster, more reliable trips? Do low-income households use it, and if so, how often, and at what price? From a policy perspective, public decision makers wish to understand the equity aspects of HOT lanes. Users of the HOT lanes pay more than non-users, but they gain travel benefits from those payments. Are the benefits of these lanes equitably distributed or not?

It is important for any transportation agency operating a HOT lane to understand the uses and benefits obtained from these systems, as well as their impacts on different groups. Monitoring the use and performance of these systems over time is also necessary to understand when changes in system operations need to occur to ensure a more equitable outcome.

The Washington State Department of Transportation (WSDOT) implemented a HOT facility along the I-405 corridor in the Puget Sound (Seattle) region in September 2015, following the implementation of one other HOT lane (SR 167) in the region, and other facilities in San Diego, Houston, Minneapolis, and elsewhere. As policies like congestion pricing and HOT lanes are more frequently implemented by cities around the world, empirical analysis is critically important. WSDOT has a vested interest in the gap of quantitative analysis that currently exists in the literature regarding how HOT facility use varies across user characteristics such as income, race, and commuting patterns.

On the basis of data from I-405 HOT lane users for all of 2018, this report aims to provide quantitative information about how the lanes are being used, how the costs and benefits of the lanes are distributed, and how changes in facility operations could affect those distributions.

Research Questions

Specifically, this report addresses the following questions:

- How do different groups of travelers differ in their usage of the I-405 HOT lane facility?
- What are the costs and benefits to those users of the facility, in aggregate?
- How are the facility's benefits and costs distributed among different groups of users?
- Are there any inequitable distributions that could be addressed by WSDOT?

When evaluating whether HOT lanes are equitable, many researchers point out that in addition to evaluating absolute equity, relative equity must also be considered via comparison against alternative methods of reducing congestion such as roadway-network expansion. Most researchers also note that whether HOT lanes are progressive or regressive depends greatly on how the revenue the lanes generate is ultimately spent. For the purposes of our study, however, we focused solely on understanding the equity of direct HOT lane use, access, costs, and benefits, while acknowledging that this is a far from complete picture of overall HOT lane equity.

Analysis Factors

Analyses could in principle be performed on dozens of different groups and at several scales of aggregation. This report focuses on usage and benefit distributions by:

- Geography
- Income
- Carpool use
- Race
- Frequency of facility use
- Time of day
- Toll

Within each of these factors, equity can be measured on a per-capita, per-trip, per-mile, and per-dollar basis. Not all of these measurements are useful in a given analysis, but this report makes comparisons when appropriate.

Data

WSDOT provided us with data on every toll plaza transaction in 2018. Each transaction record consisted of a time stamp, plaza identifier, license plate or Good To-Go! account ID, Good To Go! transponder ID (if available), whether or not the trip was an HOV, and if not, the toll paid. (All ID variables were de-identified with a cryptographic hash by WSDOT prior to delivery of the data to the research team.) WSDOT aggregated the transaction records from individual toll plazas to form trip records, which included the entry and exit times and locations for specific trips. WSDOT was also able to link a majority of user license plates and accounts to a census block group. Census block groups cover a smaller geographic area than census tracts, and are generally the size of small neighborhoods. Using that census block-group assignment, we could then link demographic information from the census to most trips in the WSDOT database. Appendix A contains summary statistics and additional data quality information.

In addition to the trip data from the express lanes, we downloaded from WSDOT facility speed and volume data, for each entry point along the corridor and for both the HOT and general purpose (GP) lanes, in 1-minute increments throughout 2018. We also downloaded travel time data for each pair of entry and exit points, for both HOT and GP lanes, in 5-minute increments.

2018 WSDOT Survey

In 2018, WSDOT surveyed 1,795 account holders, meaning both users of I-405 who paid and those who did not. The WSDOT website reported, “A random selection of participants from each target population was sent a password-protected invitation to take the online survey...customer and business survey participants were randomly selected from the Good To Go! database. All reported data has a 95% confidence level.” This survey was not a representative sample of the facility’s users. Drivers with license plates make up around 60 percent of unique users in the corridor who, given the sampling method, did not have the chance to respond to WSDOT.

Income Distribution

Given this fact, Figure 1.1 shows the income distribution for survey respondents. The distribution is bimodal, with a peak in the \$100,000 to \$125,000 and \$250,00 and over ranges. This aligns with our later estimate of median income at around \$100,000 and may demonstrate that this survey lacked respondents from lower-income brackets.

Time Savings and Reliability

The survey also provided a chance to see users’ thoughts surrounding the facility’s efficiency and value, which helped inform our analyses. As seen in Figure 1.2., when asked whether the HOT lanes “give people a reliable choice for a faster trip” and “are good value for the time they save,” respondents agreed that the facility provides more reliability than time savings. Neutral or positive responses to each question made up the majority of the sample, while strictly positive reactions to reliability were greater than those to time savings. This was not reflected in our value of time and reliability measures, but this survey only asked how well the facility provides these services.

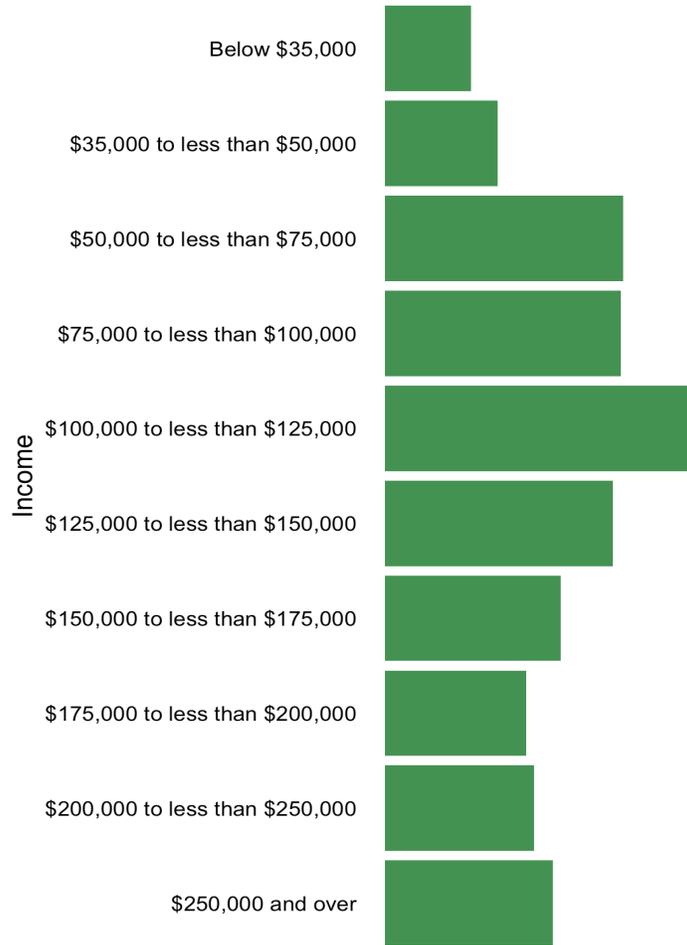


Figure 1.1. Income frequency

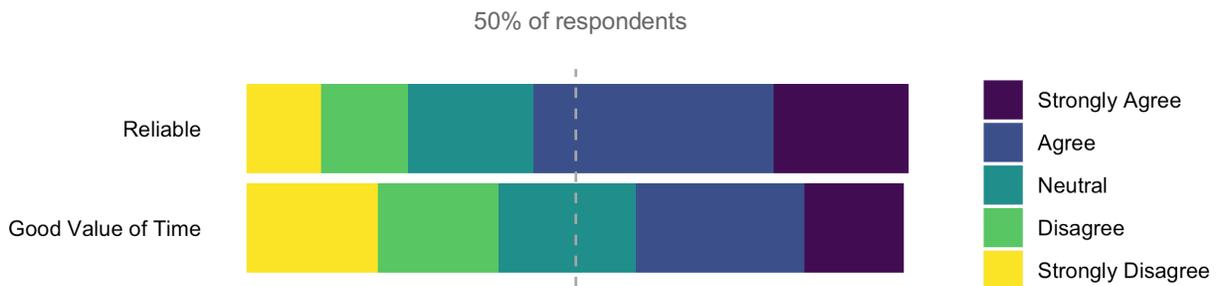


Figure 1.2. Time savings and reliability survey responses.

As shown in Figure 1.3, users of different incomes also did not meaningfully differ in their assessment of time savings and reliability across the corridor.



Figure 1.3. Time savings and reliability survey responses across incomes.

Chapter 2: Usage Patterns

Unsurprisingly, usage varies by almost every conceivable variable. The primary variables of interest for this project were geography, income, carpooling, and route.

Usage by Geography

Overall, we found few surprising geographic usage patterns. Households located closer to the facility use the facility more than those farther away, and drivers living at the north end of the facility, who primarily commute south, travel farther and pay higher tolls than those living along the southern section of the facility.

Income and Race Reference Maps

When examining maps of usage, it is useful to be able to compare usage to the region's income (Figure 2.1) and racial distributions (Figure 2.2).

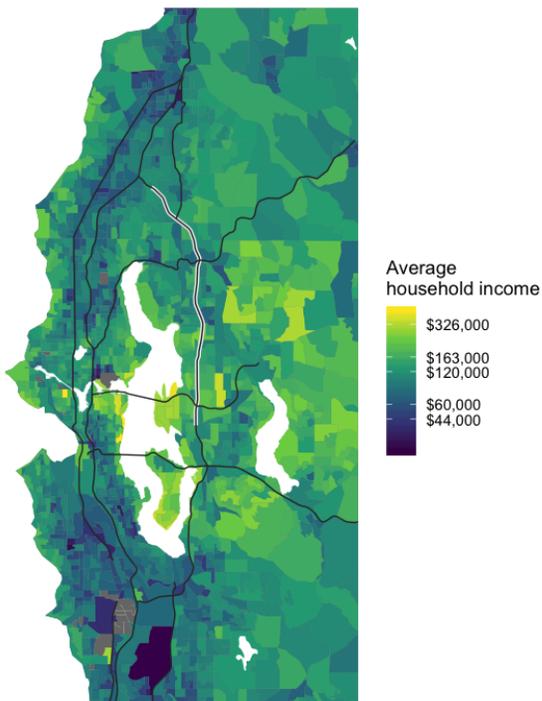


Figure 2.1. Household income.

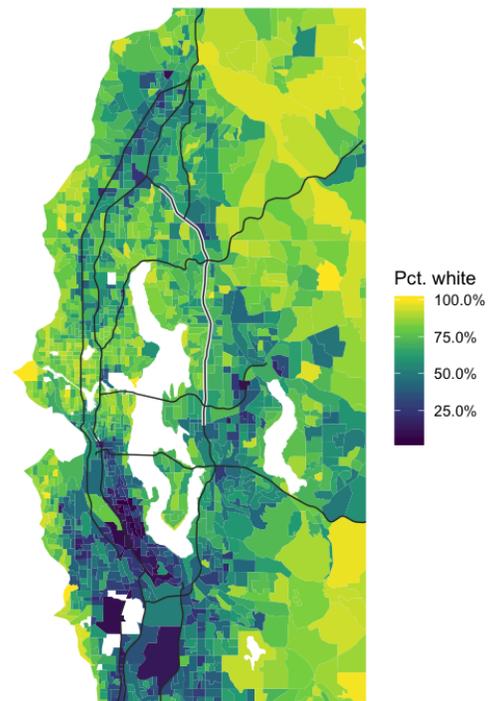


Figure 2.2. Percentage of white households.

Higher-income areas are typically clustered around the region's coastlines (Figure 2.1). Around the HOT lane facility, Bellevue, Redmond, and Kirkland are relatively high-income, whereas Lynnwood and the surrounding communities in the north are lower-income. Minorities are concentrated south of Seattle, in the southern half of Bellevue, and around Lynnwood (Figure 2.2).

Number of Trips

As Figure 2.3 shows, facility users live mostly in the upper half of the facility, concentrating around the I-405 / SR 522 interchange. (Note that the users of the facility “live” at the location where either the Good To Go! account being used is registered or the vehicle license plate is registered.) Significant usage is also clustered around the Port of Seattle and the industrial area south of I-405, between I-5 and SR 167.

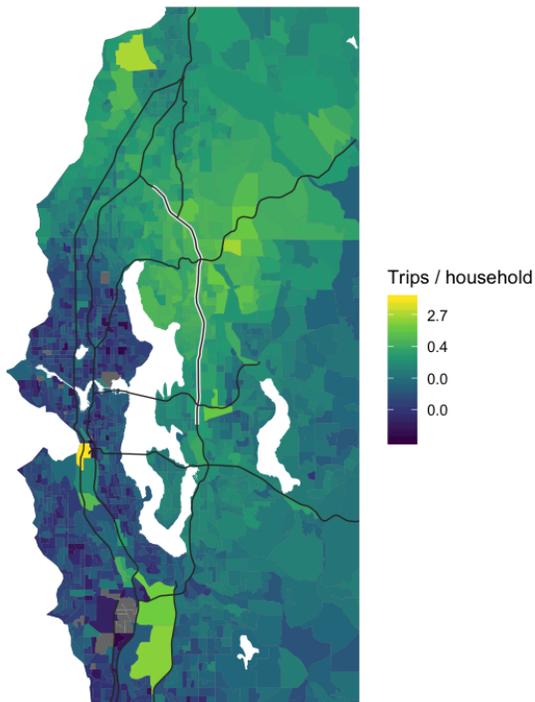


Figure 2.3. Trips per household.

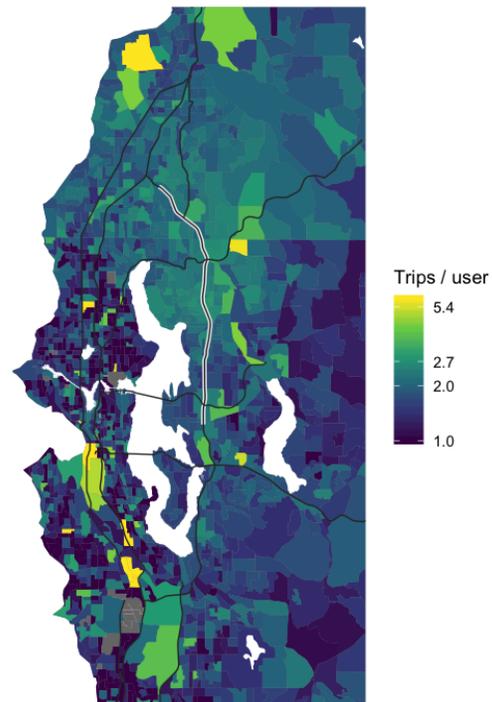


Figure 2.4. Trips per user.

Figure 2.4 shows where the most frequent users live. Again, we see clusters in the industrial areas extending south of downtown Seattle and north by Paine Field. Frequent users also live just east of the SR 522 interchange with I-405.

Average Toll and Trip Distance

The general pattern of commuting on the facility is southbound in the morning and northbound in the evening. In addition, the facility’s northern end has only one HOT lane in each direction, whereas the southern section consists of two HOT lanes in each direction. This results in the northern section of the HOT lane often having a greater demand/capacity ratio, and as a result of the dynamic pricing algorithm, a higher price. Consequently, users living north of the facility generally travel both farther and through more congestion than users living farther south along the corridor. This is reflected in the average toll paid, shown in Figure 2.5, which is highest for users living in Snohomish County, west of I-5.

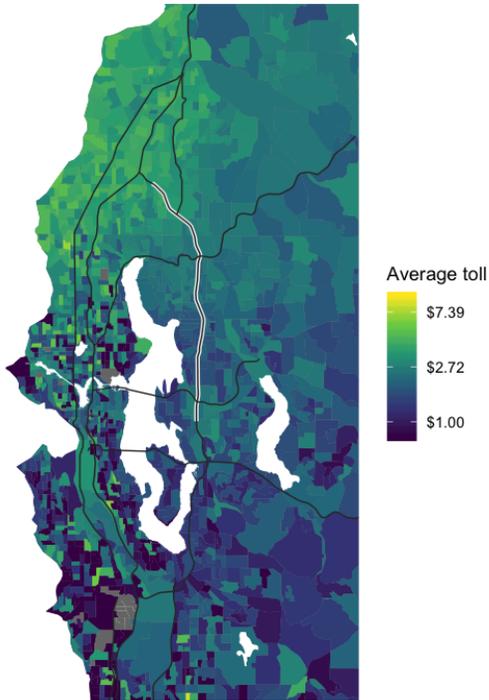


Figure 2.5. Average toll per trip.

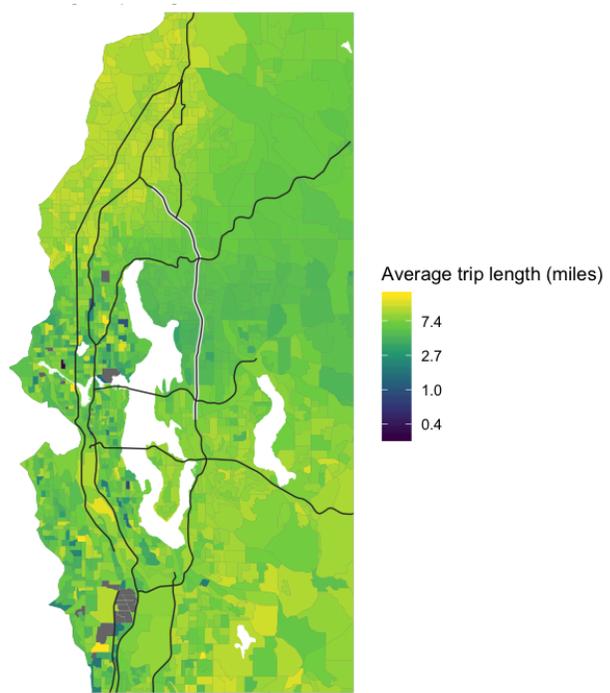


Figure 2.6. Average trip length.

Unsurprisingly, average trip distance on the toll facility is higher for users living at the ends of the facility than users living toward the middle (Figure 2.6). Users making the longest trips on average typically live north of the facility, in Snohomish County, west of I-5. There are very few areas where the average trip length falls below 2 miles, and most of these are likely attributable to statistical noise.

Usage by Income

Overall, as might be expected with any tolling system, higher-income households use the facility more than lower-income households do. Nevertheless, we found some surprising patterns in income distribution by toll and by overall frequency of use. (See Appendix B for methodology details.)

Regional Income Distribution

The ability to estimate distributions of income on the facility becomes especially useful when there is a reference income distribution for all I-405 drivers. Without such a reference distribution, comparisons between the HOT lane user population and the general population become more difficult, and conclusions about equity of usage more complicated.

Our preferred method of constructing a reference distribution involved data on traffic analysis zones (TAZs) provided by the Puget Sound Regional Council (PSRC). PSRC's "4k model" would have allowed the agency to construct a "travel shed" of TAZs, weighted by the number of trips

made on I-405. Using available demographic information on each TAZ, we could have then constructed an income reference distribution.

Unfortunately, PSRC was not able to produce a travel shed analysis in time for our work. We therefore approximated the I-405 travel shed by comparing our estimated income distributions to the distribution of income in King and Snohomish counties. The median household income across these two counties is approximately \$84,000 per year.

Number of Trips

We estimated that the median household income of noncommercial⁴ HOT lane users is approximately \$101,000 per year, around 20 percent higher than the median household income of King and Snohomish counties. As Figure 2.7 shows, 15 trips are made for every 1,000 households in the region making \$50,000 per year, while 35 trips are made for every 1,000 households making \$200,000 per year, a 133 percent increase. However, most facility trips are not made by high-income households. We estimated that over 80 percent of facility users have an income below \$200,000 per year.

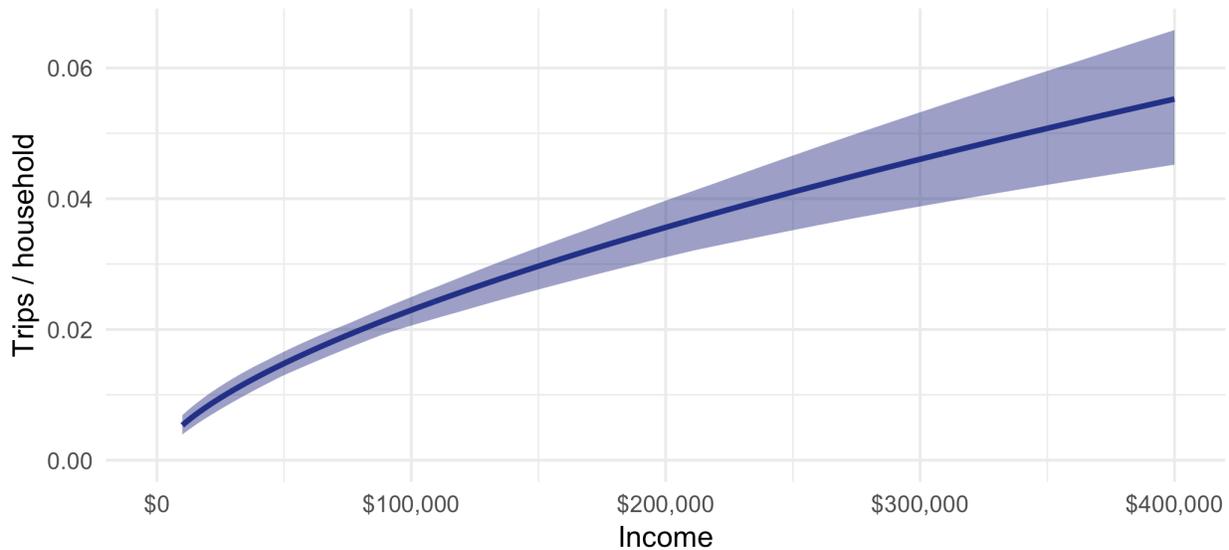


Figure 2.7. Trips per household, by income.

⁴ WSDOT does not label facility users or trips as either “commercial” or “noncommercial.” However, commercial Good to Go! accounts are available to businesses who need more than six Good to Go! passes. We therefore consider all accounts with six or fewer registered passes as “noncommercial,” recognizing that this group likely includes many small businesses.

Paying Versus Carpooling Users

Paying users have a slightly higher median income than carpooling users do (Figure 2.8). This is altogether not too surprising, as carpool users do not face any economic burden in using the HOT lanes. However, the difference is not large, especially in comparison to the income level for the surrounding counties. SOVs make up 72 percent of all vehicle trips, and HOVs make up the remaining 28 percent.



Figure 2.8. Median income of carpoolers versus paying customers.

Time of Day and Direction

Users may be classified into “AM peak” (southbound from 5:00 a.m. – :00 a.m.), “PM peak” (northbound from 3:00 p.m. – 7:00 p.m.), or “Off-peak,” which consists of reverse direction-commuters and all trips between 9:00 a.m. and 3:00 p.m. Given these classifications, peak users of the facility have significantly lower incomes than off-peak users, especially morning peak users (Figure 2.9).



Figure 2.9. Median income by peak or off-peak facility use

The income difference between morning and afternoon peak commuters may be explained partially by traffic patterns. Table 2.1 shows the average travel time savings for sections of the facility, southbound at 7:30 a.m. and northbound at 5:00 p.m. In the morning, time savings are relatively higher in the one-lane section, where incomes are lower, while in the afternoon, time savings are relatively higher in the two-lane section, where incomes are higher.

Table 2.1. Average travel time savings by facility section and direction.

	Southbound at 7:30 a.m.	Northbound at 5:00 p.m.
One-lane section (north)	9.6 minutes	3.9 minutes
Two-lane section (south)	5.6 minutes	13.0 minutes

We examined these patterns in more granularity by looking at each hour of the day, in each direction. In Figure 2.10, each point is a median income estimate for a particular hour of the day and direction of travel. Larger circles indicate higher vehicle volume. The estimates presented in Figure 2.10 are more uncertain than in Figure 2.9, but the general trends are the same: morning commuters, especially from 5:00 – 7:00 a.m., have significantly lower incomes.

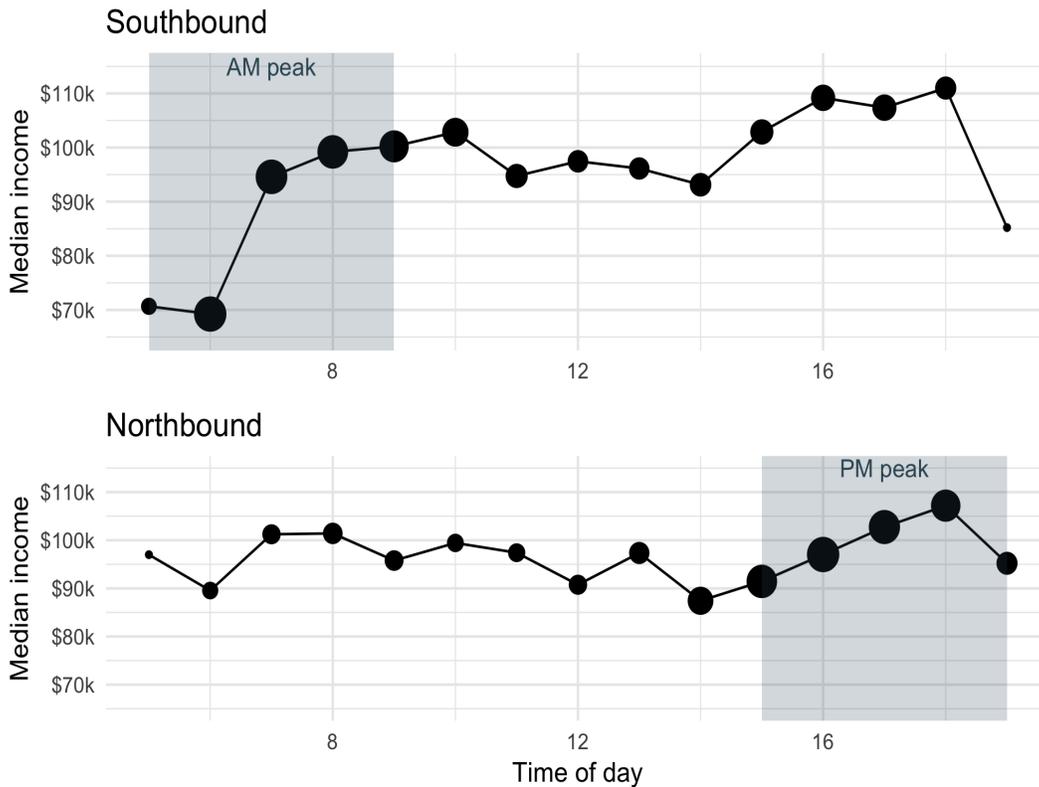


Figure 2.10. Median income by direction and time of day of use.

Toll Paid

Income patterns by toll paid were more surprising. While one might expect that the median income would rise with higher tolls, in fact, the opposite is true. As Figure 2.11 shows (toll amounts are rounded up to the nearest dollar), median household income is highest for tolls of \$0.75 and \$1.00, at \$128,000 per year. On the other end, income is lowest for tolls of \$10, with a median income of \$61,000 per year, much lower than the median for the surrounding area, and less than half the median for the lowest tolls.

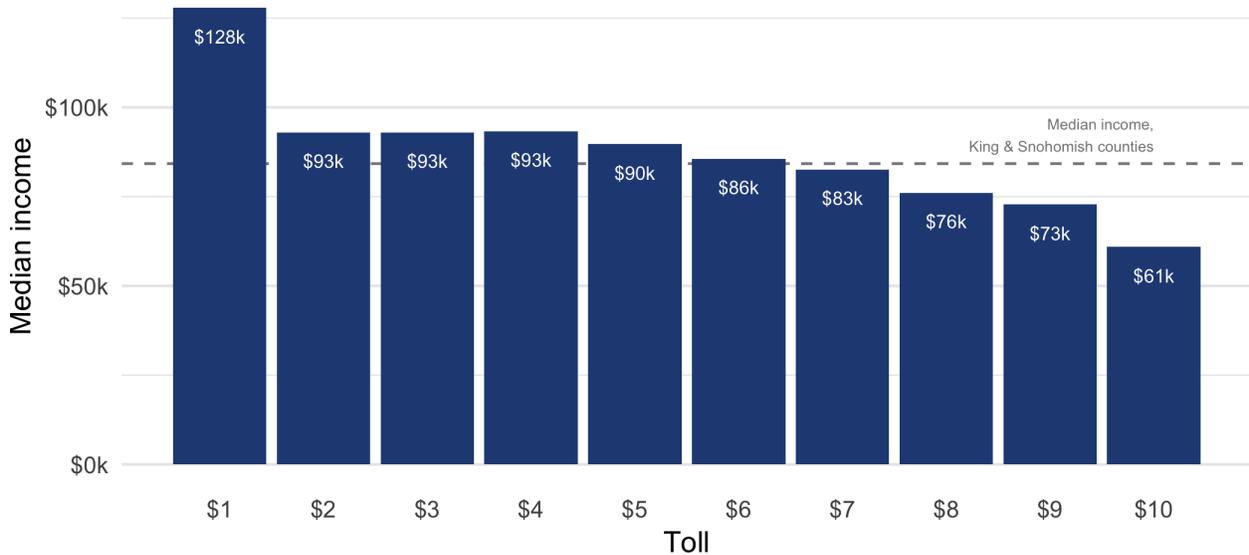


Figure 2.11. Median income by toll paid, rounded up to the nearest dollar.

Frequency of Use

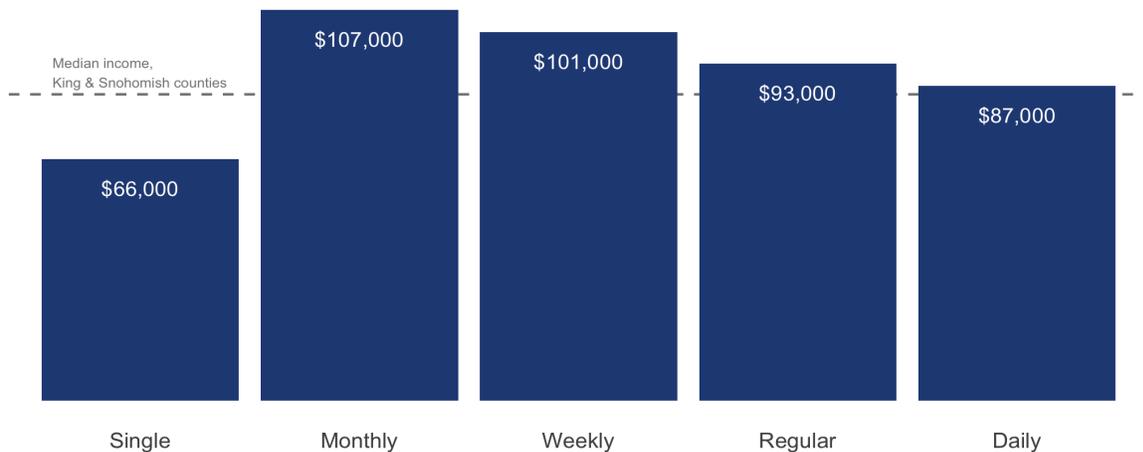
Of all paying trips in the WSDOT database, 84 percent had a unique user identifier. This user identifier allowed us to classify noncommercial users by their overall usage of the facility, which we divided into six groups, as shown in Table 2.2.⁵

⁵ High-frequency users were removed from graphics, as this population likely consists of commercial users and transit vehicles, for whom “household income” is not relevant.

Table 2.2. Frequency of use category definitions and summary statistics.

In 2018	Frequency category	Fraction of accounts	Fraction of trips
1 trip	single	48.2%	2.9%
Between 2 and 40 trips	monthly	43.7%	20.6%
Between 41 and 120 trips	weekly	4.7%	20.0%
Between 121 and 250 trips	regular	2.1%	22.4%
Between 251 and 600 trips	daily	1.1%	23.5%
Over 600 trips	high	0.1%	10.6%

Figure 2.12 shows the median income for each of the five main user frequency groups. One-time users have the lowest incomes, and monthly users have the highest incomes. The patterns for HOV users (not shown) are nearly identical.

**Figure 2.12. Median income for paying users by frequency of use in 2018.**

The picture grows more complicated, however, when the same plots are made at the county level (Figure 2.13). In King County, higher-frequency users also have lower incomes than lower-frequency users. However, in Snohomish County, the trend is reversed. The pattern in Snohomish is more in line with expectations: higher-income households can afford to use the facility more frequently. It is not clear why the pattern reverses, but note that Snohomish County users are mostly commuters, whereas there is more variation in King County.

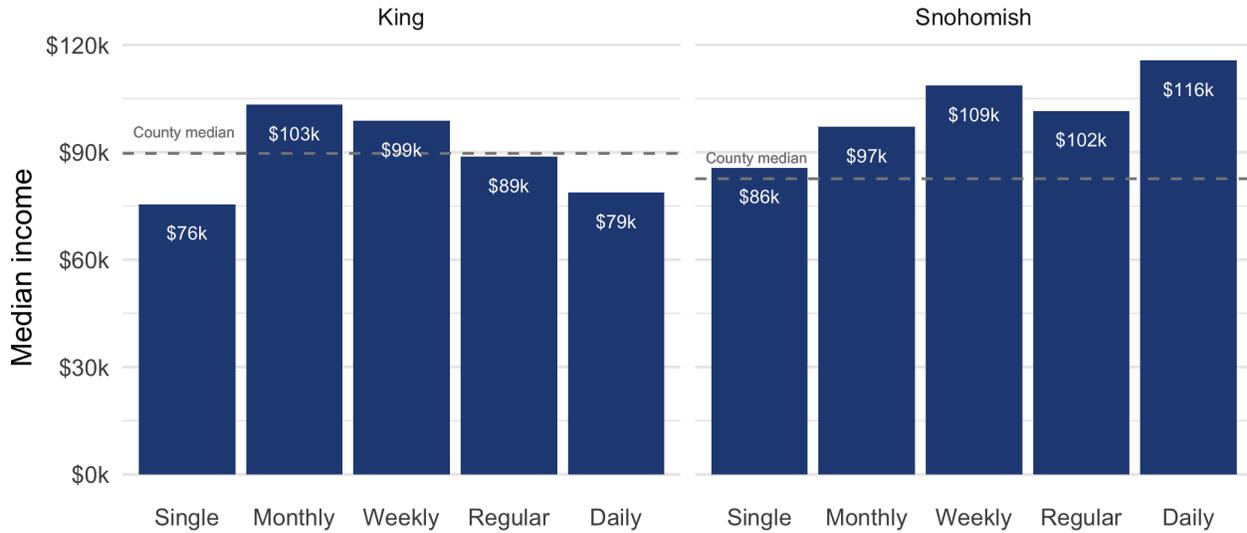


Figure 2.13. Median income for paying users by county and by frequency of use in 2018.

Regardless of the county pattern, however, one-time users are clearly much more representative of the overall population than drivers who use the facility more than once. When time savings are crucial, anyone—higher or lower income—can pay to avoid congestion. Indeed, most one-time users pay through their license plate, rather than from an online account set up in advance. From an equity perspective, the fact that this pool of one-time users is more representative and uses the facility on an ad-hoc basis suggests that the facility does indeed provide valuable choice to all drivers.

Usage Differences Between Paying and Carpooling Users

Paying and carpool users are largely divided into two distinct groups, as Table 2.3 shows. Only 7.6 percent of users made both a paid and a carpool trip in 2018.

Table 2.3. Classification of users by SOV and HOV trips made in 2018.

Group	Percentage of users
Carpool only	20.1%
Paying only	72.3%
Both carpool and paying	7.6%

Time of Day

As Figure 2.14 shows, the share of HOT lane traffic made up of HOVs varies substantially throughout the day, and by direction of travel. HOV usage as a percentage is highest northbound in the late morning, at over 35 percent of total HOT lane volume. HOV usage is lowest southbound during the early morning peak, at less than 25 percent of HOT lane volume.

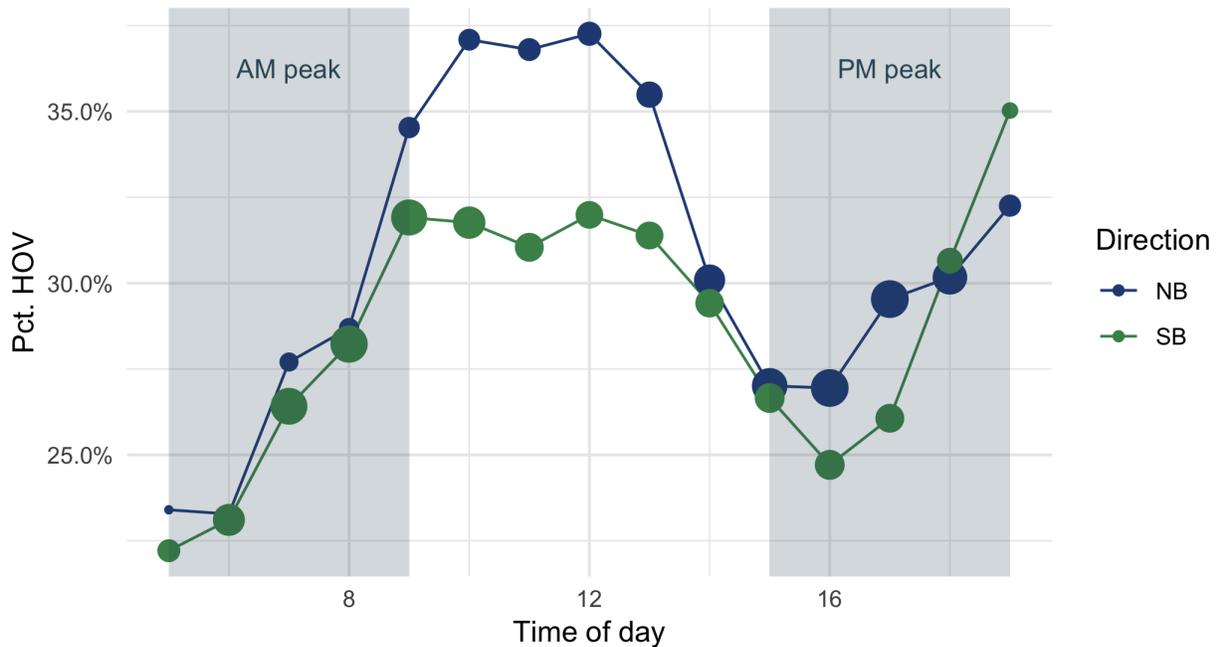


Figure 2.14. Percentage of trips which are HOV by direction and time of day.

In general, commuters travel alone, while many off-peak users have children or other family members in the car. Additionally, congestion is worst during peak periods, pushing SOVs into the HOT lanes. Together, these patterns help explain the trends observed in Figure 2.14.

Frequency of Use

Using the frequency of use definitions in Table 2.2, Figure 2.15 shows the proportion of paying and carpool users in each frequency category.

Nearly all one-time users pay, and the fraction of paying users decreases with frequency. These patterns are in line with expectations. Paying users have no up-front cost but must pay for each additional trip. Carpoolers, in contrast, must pay \$15 for a Flex Pass, but they pay nothing for each additional trip. Carpooling also requires a prior expectation to use the facility for carpooling, whereas the ability to pay-by-plate allows any traveler to spontaneously take advantage of the HOT lanes when their immediate need for travel time savings or reliability motivates them to use the facility.

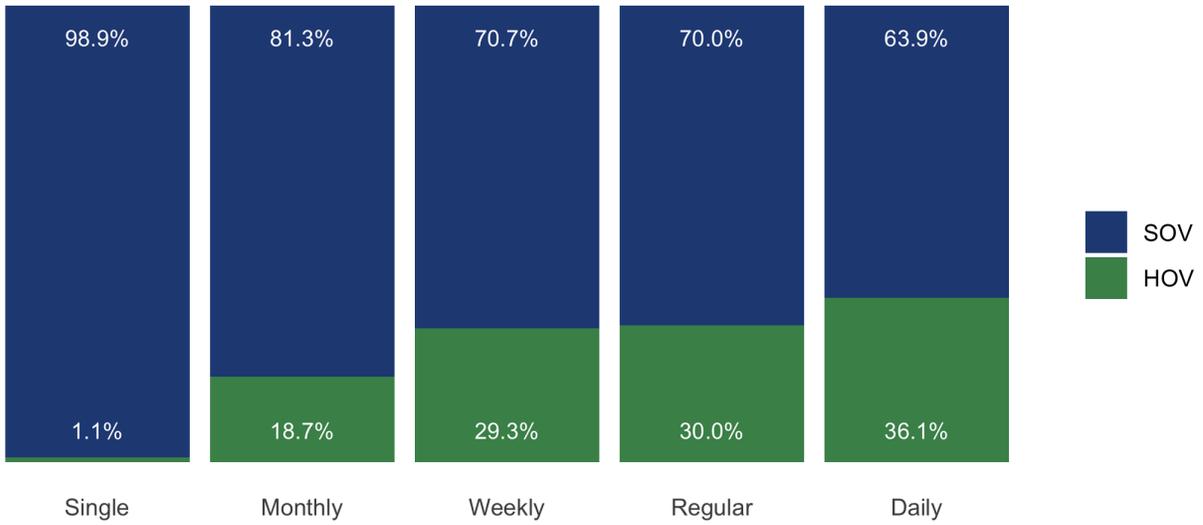


Figure 2.15. Fraction of trips made by paying (SOV) and carpool (HOV) users, by frequency of use.

Usage by Route

While many geographical usage patterns map predictably onto routes, there are some interesting trends that are best illuminated at the route level. For reference purposes, we include a map of the facility, with toll plazas, entry plazas, and exit points labeled (Figure 2.16).

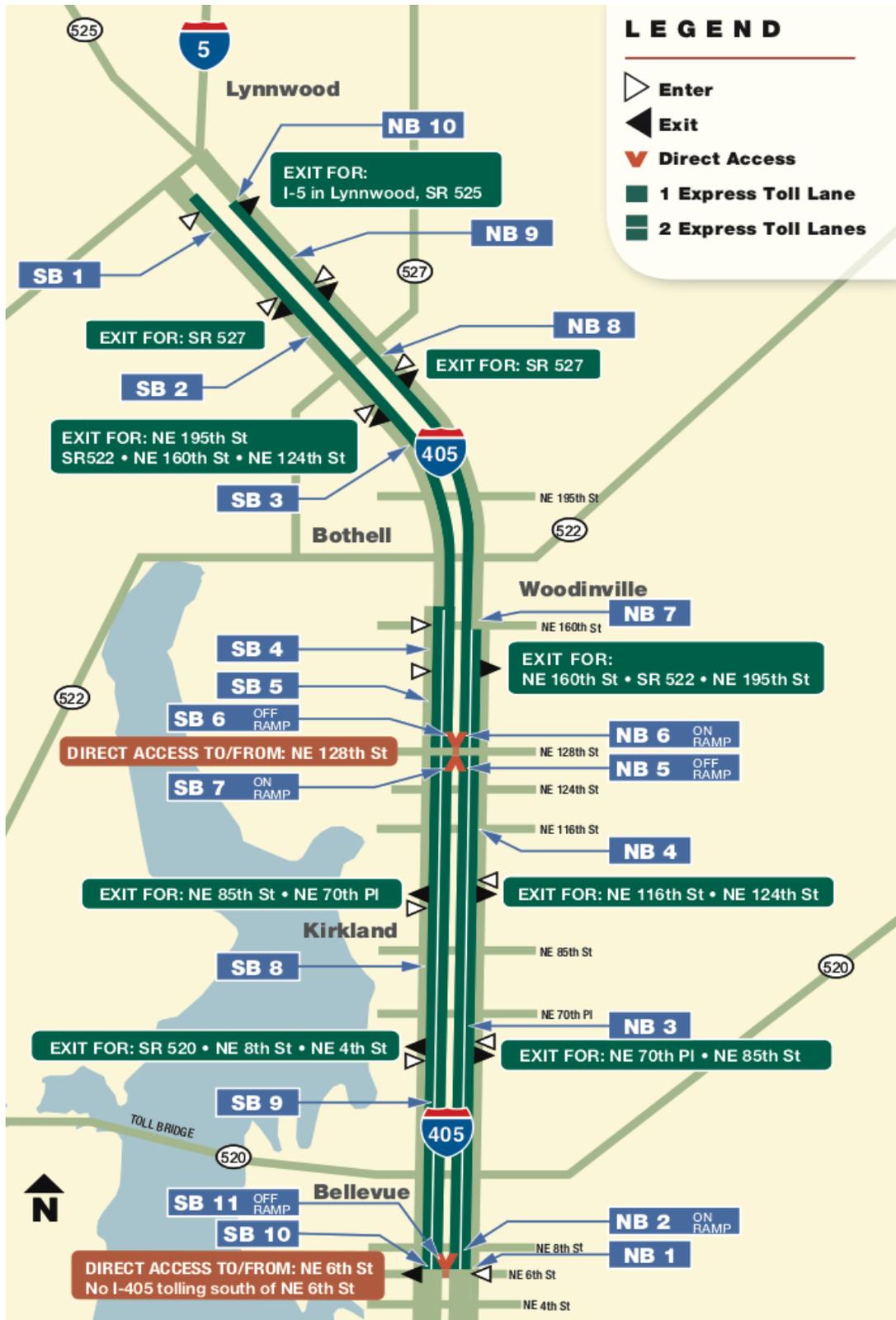


Figure 2.16. Facility map.

Overall Volume

Figure 2.17 shows overall vehicle volumes by route and time of day. Each square is a route, positioned at the intersection of its entry and exit plaza. With this layout, longer trips are in the upper-left corner, and shorter trips are along the diagonal. The size of each square is proportional to the volume of traffic along the corresponding route. Similarities along columns correspond to entry patterns, and similarities along rows correspond to exit patterns.

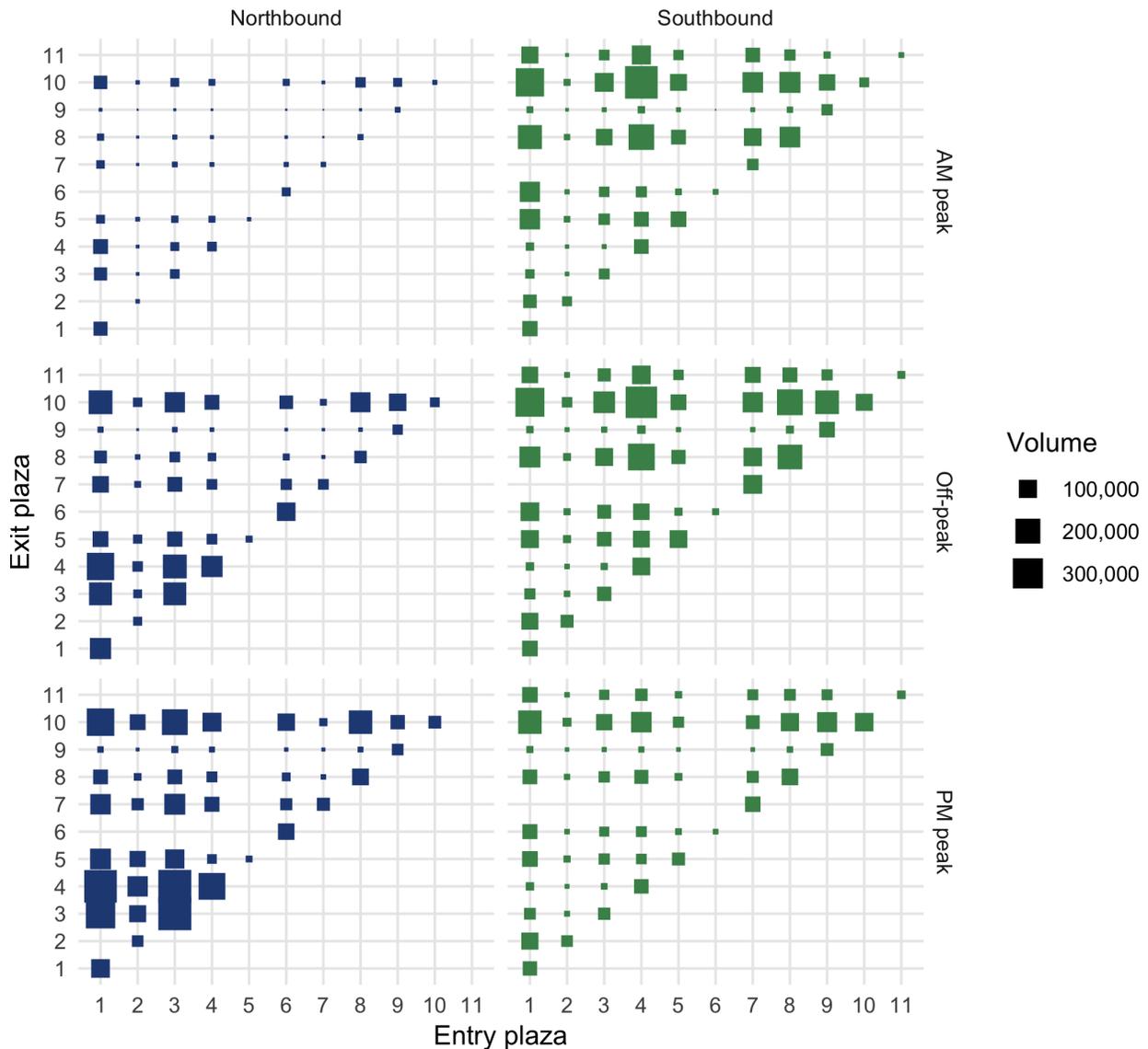


Figure 2.17. Trip volume by route and time of day.

Figure 2.17 shows that usage is highest southbound in the morning and northbound in the afternoon, although there is significant usage off-peak and southbound in the afternoon. Morning northbound usage is quite low.

Many southbound users enter at plaza 1, at the start of the facility, where the HOV lane transitions into the HOT lane. Many also exit at plaza 10, which corresponds to the point where the HOT lane transitions into the HOV lane that continues south of downtown Bellevue. The largest-volume southbound trips are the full-corridor trip and the trip from the SR 522 interchange through the end of the corridor. In contrast, while many northbound users do travel to the end of the facility at plaza 10, the largest-volume trips exit at plaza 3 (Kirkland) and plaza 4 (SR 522 interchange).

Toll Cap

The Washington State Legislature has capped the maximum toll that may be charged on the facility at \$10.00. Figure 2.18, constructed the same way as Figure 2.17, shows the fraction of trips on each route that are charged the maximum toll. Routes that include the one-lane section of the facility are colored blue, and routes that use only the two-lane section are colored green. Different entry and exit patterns by direction are clearly visible in Figure 2.17.

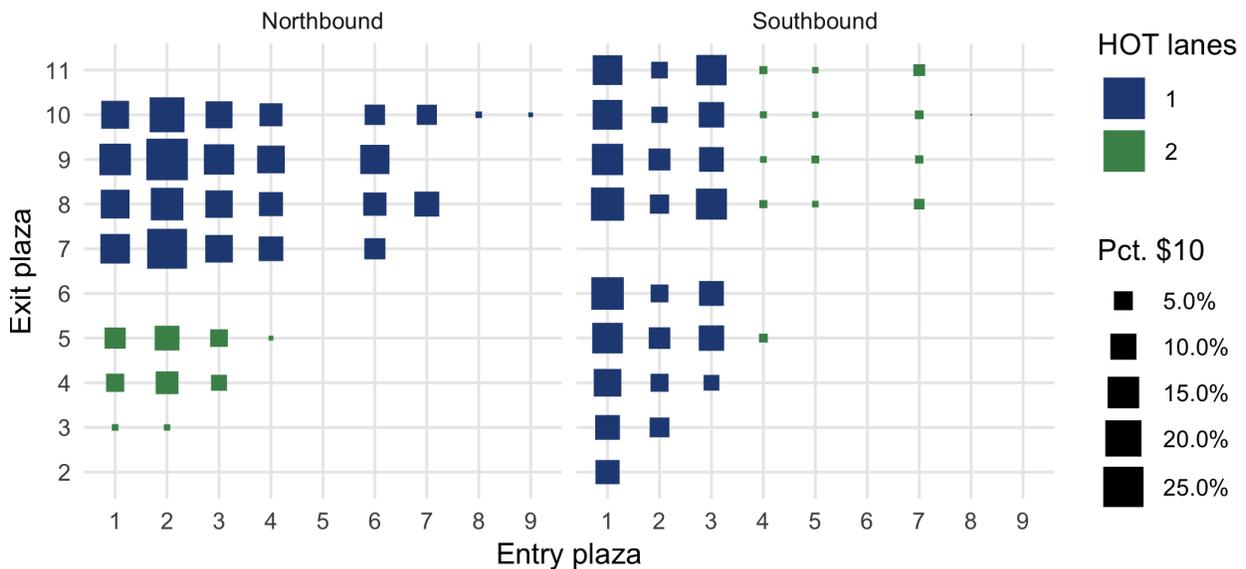


Figure 2.18. Fraction of trips charged \$10.00, by route, colored by facility section (one or two lanes).

Southbound, the toll hits its cap at a much higher rate when the entry plaza is in the one-lane section (at or before plaza 3). The toll is rarely \$10 anywhere else along the southbound facility. Northbound, the toll hits \$10 at a higher rate when the exit plaza is in the one-lane section. Since the general commute pattern is southbound in the morning and northbound in the evening, we would indeed expect to see these patterns grouped by southbound entry and northbound exit. Interestingly, northbound trips from the NE 6th Direct Access Ramp (DAR) hit the \$10 cap more frequently than any other route.

Peak Use

Figure 2.19 shows the fraction of trips on each route that are made during the directional peak periods. Across the board northbound usage occurs more during peak hours. A higher fraction of peak trips is made from the NE 6th DAR than elsewhere.

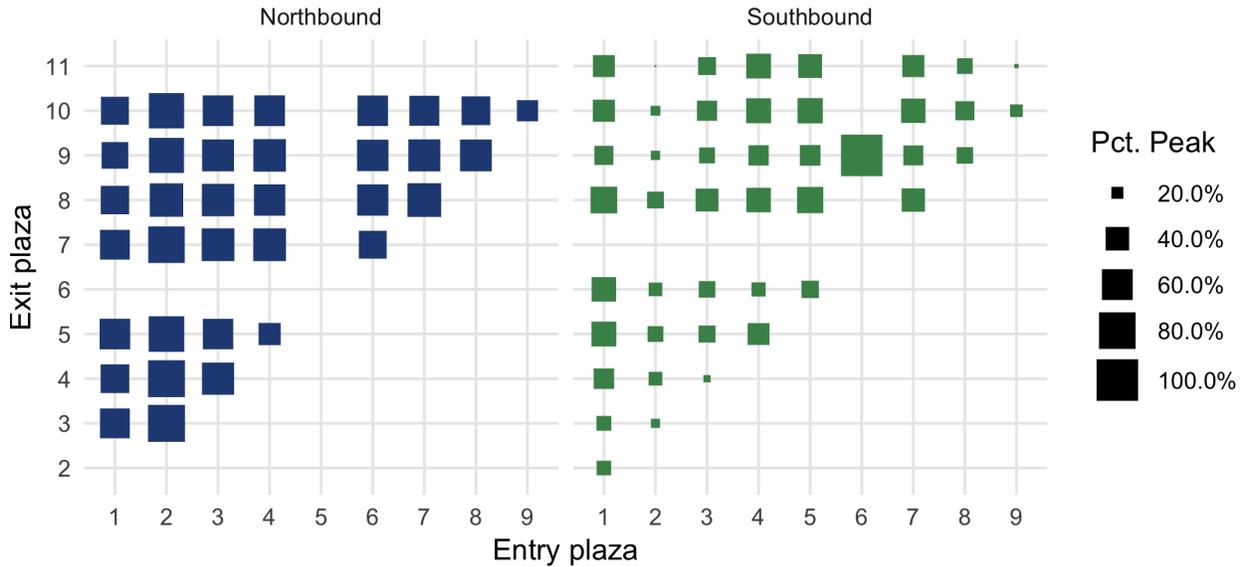


Figure 2.19. Fraction of trips made during peak period (southbound 5:00 – 9:00 a.m., northbound 3:00 – 7:00 p.m.) by route.

Southbound, the highest fraction of peak trips occurs on a technically illegal route. In this case, a significant number of vehicles enter at the NE 128th DAR and exit from the HOT lanes after passing the NE 70th gantry but before the downtown gantries. It is unclear whether these users are headed to the SR 520 ramps, or they wish to exit at NE 8th and are using the HOT lanes to avoid congestion in the GP lanes through the SR 520 interchange. Other than this anomaly, peak usage is relatively consistent, but is noticeably lower on routes originating from entry plaza 2. Presumably during peak hours, commuters enter the HOT lanes at the previous entry plaza instead of waiting the extra 1.3 miles.

Chapter 3: Overall Facility Benefits

An understanding of how HOT lane usage varies by geography and income is not enough to determine the equity of the facility. While knowing how different groups use the system is important, facility usage is not an end in itself; rather, it is a means to achieve time savings and increased reliability. Any study of facility equity must attempt to quantify these benefits and compare them to the costs of the tolls that users pay.

Modeling HOT Lane Usage

Our model measured the number of users who entered the HOT lane in 2-minute increments over the course of 2018 for each possible route. We built on the model used by Daniel Brent and Austin Gross in their paper, “Dynamic Road Pricing and the Value of Time and Reliability.”⁶ To quantify the situation a driver faces when deciding to enter the lane, we used the estimated time savings, estimated reliability, toll, speed and volume of the general purpose lanes, and the length of the trip in miles to predict the number of drivers entering the facility at a given time and at a specific entry point. From this model, we calculated the average value of time, value of reliability and price elasticity for the corridor (see Appendix C for more information and methodology).

Value of time (VOT) and Estimated Time Savings

VOT is difficult to measure given the differences between achieved travel time savings (how much time a person actually saves by going in a HOT lane) and estimated travel time savings (how much time a user *thinks* s/he will save when deciding to use the HOT lane).

To help overcome this problem, we modeled estimated time savings as a function of the visual cues available to potential users at the point in time and space where they make the decision to enter the HOT lanes—the current toll, the time of day, the route, the speed and volume of the general purpose lanes at that location, and the speed and volume of the HOT lane. We added the toll because this may be a driving factor in whether a person chooses to use the facility; if the toll is high, it may signal to the user that worse traffic is in the general purpose lanes ahead. DAR entries were excluded from our models because drivers there have very limited access to local traffic information. Figure 3.1 shows the relationship between actual and estimated time savings.

A simple VOT can be obtained by dividing the toll by the achieved travel time savings, but previous studies demonstrated that this can overinflate the effect to amounts greater than \$100 per hour. To obtain a more precise estimate, we used the model’s estimated effect of time savings and

⁶ Brent, Daniel A., and Austin Gross. 2018. “Dynamic Road Pricing and the Value of Time and Reliability.” *Journal of Regional Science* 58 (2): 330–49. <https://doi.org/10.1111/jors.12362>.

divided it by the negative effect of price.⁷ This yielded a VOT based on estimated time savings at a much more reasonable rate.

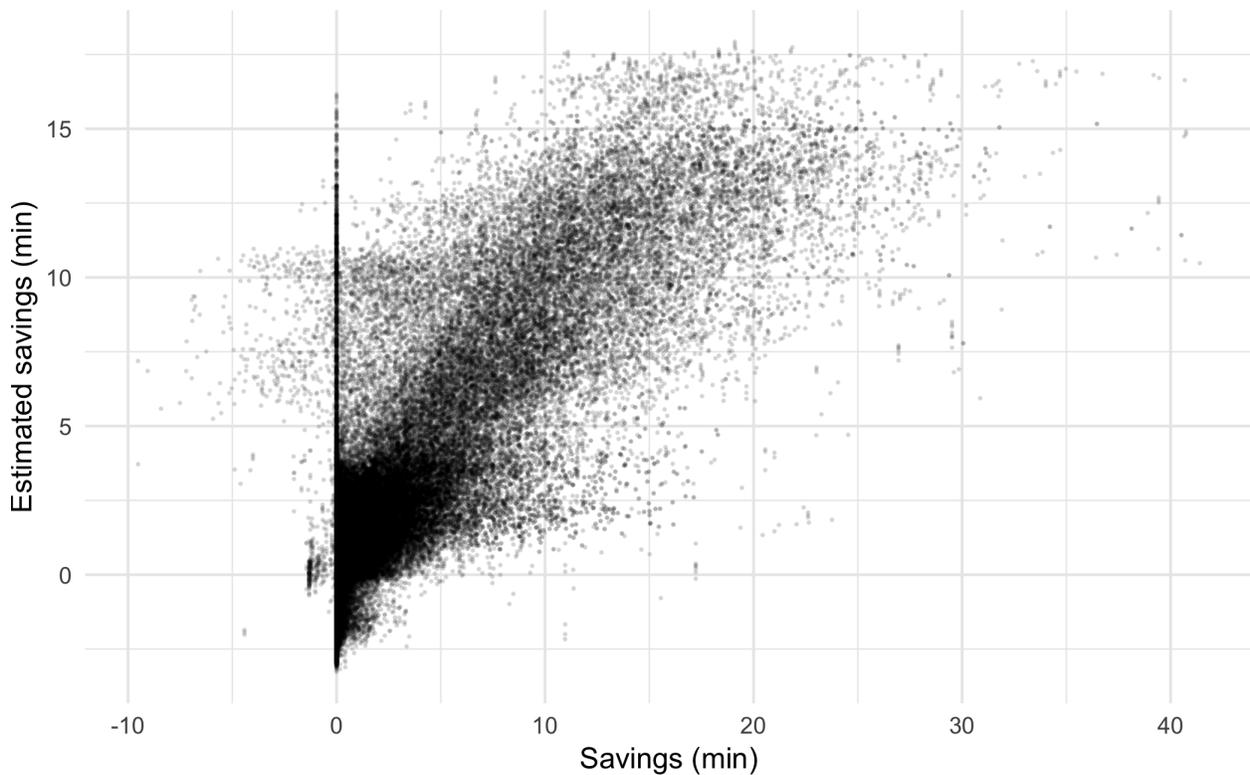


Figure 3.1. Actual versus estimated time savings, in minutes. Plot margins show marginal densities.

Value of Reliability (VOR) and Estimated Reliability

Reliability determines how well the facility functions for a user. To visualize this effect, it is useful to imagine a commuter who knows that the commute takes a certain amount of time each day, and also knows that the commute time can vary depending on different traffic conditions such as weather. We attempted to quantify this variability in commute times by taking the difference of the 80th and 50th percentile travel times for both HOT and general purpose lanes in a given time of day. The difference of these values for each lane provided reliability estimates.⁸ The more reliable a commute is, the less variability there will be in travel time.

Figure 3.2 shows average time savings and reliability estimates in 15-minute increments for full-corridor trips in each direction. Generally, time savings and reliability correlate well, but during

⁷ This represents the marginal rate of substitution between time and money. Brent and Gross (2018) also described this as an estimate of the marginal utility of buying into the toll (“negative one times the dis-utility of the toll”), also defined as the marginal utility of income lost.

⁸ This is also known as the mean-variance model from Small, Kenneth A., Clifford Winston, and Jia Yan, “Uncovering the Distribution of Motorists’ Preferences for Travel Time and Reliability,” *Econometrica*, 2005, 73 (4), 1367–1382.

certain sections of peak hours, reliability drops. This probably reflects the continued difficulties in maintaining HOT lane performance along the corridor during periods of high demand.

In a method similar to VOT estimates, we used the effect of reliability and divided it by the negative effect of price to obtain the VOR.⁹

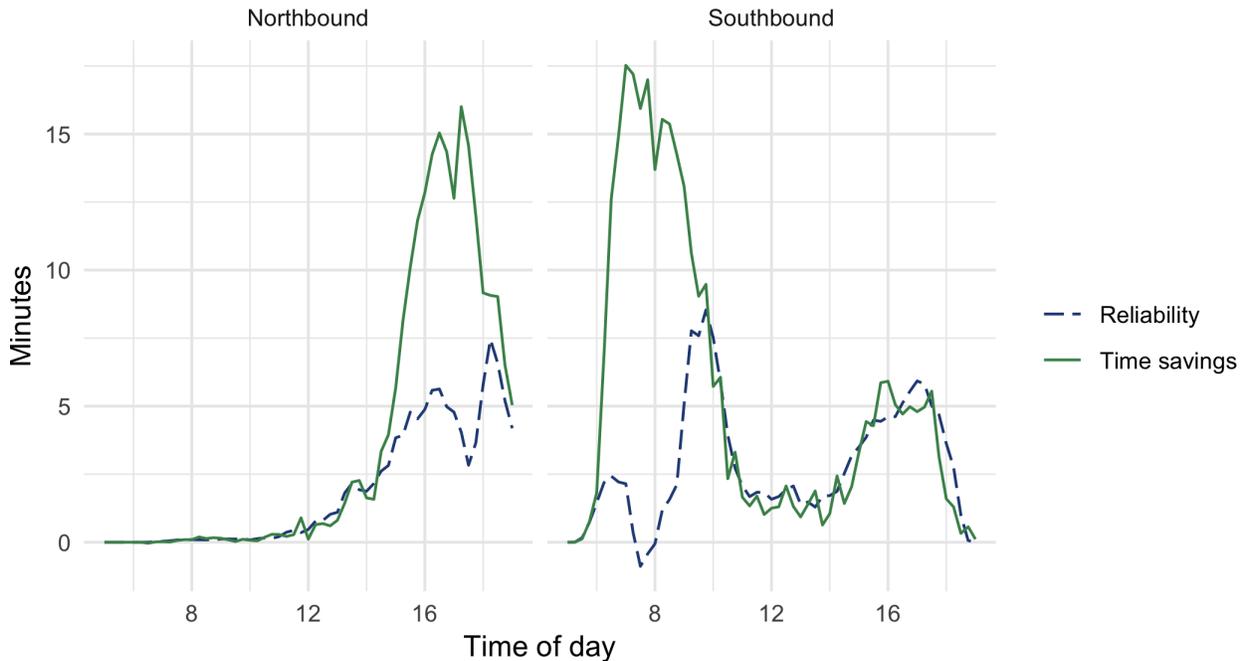


Figure 3.2. Time savings and reliability estimates in 15-minute increments for full-corridor trips in each direction.

Price Elasticity

Price elasticity of demand describes changes in user behavior when users are faced with a change in price. Negative values represent economic goods that follow a normal demand curve: an increase in price decreases demand. Previous studies of toll lanes have estimated positive price elasticity, meaning the opposite: demand increases as price increases. Brent and Gross (2018) attributed this to studies not controlling for the occurrence of increases between toll and volume. That is, more people likely do not opt to use the toll lane solely because the price is higher, but rather because both volume and price increase as a result of increased traffic, and therefore the HOT lane becomes a more desirable good.

⁹ As with VOT, this represents the marginal rate of substitution between reliability and money.

Overall Findings

Table 3.1 presents our estimates for VOT, VOR, and price elasticity. As noted above, the estimated median income for facility users is \$101,000 per year, which corresponds to an hourly rate¹⁰ of \$49 per hour, very close to our VOT estimate of \$53 per hour. Our estimated VOR is \$26 per hour, just under half the VOT. The price elasticity for users is estimated to be -0.64 . This means that a 10 percent increase in toll would, on average, decrease HOT lane demand by 6.4 percent.

Table 3.1. Model estimates for VOT, VOR, and price elasticities, along with 95% confidence intervals.

Parameter	Point estimate	Range
VOT	\$53 per hour	\$52 to \$54 per hour
VOR	\$26 per hour	\$24 to \$29 per hour
Price elasticity	-0.64	-0.67 to -0.61

It is important to note that this elasticity estimate only applies on average, across all trips and times. The marginal price elasticity at a given roadway segment, given a certain toll level, may be quite different. In particular, price elasticity at the upper end of the toll scale, near the toll cap of \$10, is almost certainly not -0.64 .

Differences by Time of Day

We also estimated VOT, VOR, and elasticity by time of day and direction—southbound morning peak users (“AM peak”), northbound afternoon peak users (“PM peak”), and all other users (“Off-peak”). The estimates are displayed in Figure 3.3.

Morning and afternoon peak elasticities are relatively similar, but the estimated off-peak elasticity is much lower, at only -0.30 . This is most likely due to the higher percentage of higher-income users and small commercial users¹¹ in the off-peak; both of these groups are likely less sensitive to price than the average user because the toll represents a smaller proportion of their disposable income. Additionally, the toll is generally lower during off-peak hours, and at lower tolls users are likely to be less sensitive to price.

¹⁰ Assuming a 2,080-hour work year.

¹¹ Large commercial users were filtered out of the analysis, but we were unable to remove small commercial users (see footnote 4).

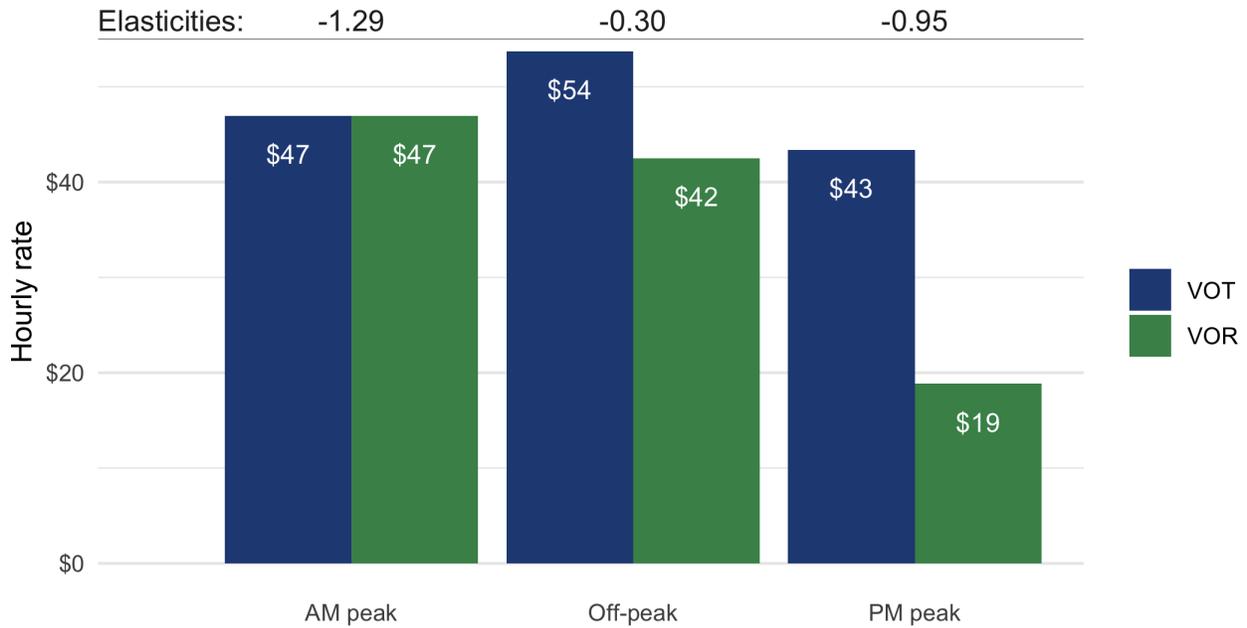


Figure 3.3. VOT, VOR, and elasticity estimates by time of day and direction.

Aggregate Benefits

In modeling driver behavior and estimating VOT, VOR, and elasticity, we used estimated time savings. But once a trip has been completed, we could use the estimated VOT and VOR, and achieved time and reliability savings, to assign a monetary value to the trip. Subtracting the toll paid, we arrived at a net benefit per trip. Table 3.2 summarizes these benefits for SOV users, both in aggregate and on average per trip.

Table 3.2. Average and aggregate time savings, reliability, toll, and net benefit.

	Per trip	Aggregate
Time savings	3.81 minutes	763,000 hours
Value of time savings	\$3.38	\$41M
Reliability gain	1.74 minutes	349,000 hours
Value of reliability gain	\$0.77	\$9M
Total benefit	\$4.15	\$50M
Toll	\$2.57	\$31M
Net benefit	\$1.58	\$19M

Net benefit per trip is positive, indicating that on average users receive more benefits from the system than the toll they pay. Of the average total benefit of \$4.15 per trip, 81 percent is provided in the form of travel time savings, and only 19 percent comes from reliability gain.

The previous section demonstrated that VOT and VOR vary by time of day. We would also expect VOT and VOR to vary by income, location, and other key variables. Unfortunately, the aggregate nature of the demographic data provided to us did not allow us to estimate differing VOT and VOR for these groups. Consequently, we computed per-trip and aggregate benefits by assigning all facility users the same average VOT and VOR.

From an equity perspective, however, this is not a problem. Assuming different VOT and VOR for different groups of users would skew any analysis in favor of the group that placed a highest value on their benefits. In this case, that group would probably be higher-income users. Any such difference in VOT and VOR would therefore tend to lead to a foregone conclusion that the HOT lane facility was equitable. By assigning each trip the same average VOT and VOR, we avoided this problem

Chapter 4: Distribution of Facility Benefits

The previous two sections analyzed usage patterns and overall facility benefits. While interesting in their own right, it is only at the intersection of these two axes of analysis that we can understand the equity of the express toll lanes.

Geographic Distribution

As will be clear below, ultimately geography plays only a small role in the distribution of net benefits per trip. However, there are still several interesting geographical patterns.

Time and Reliability Savings

Geographic patterns in time and reliability savings largely mirror the patterns in average toll shown previously in Figure 2.5. The largest time savings per trip accrue to users living northwest of the facility, west of I-5 (Figure 4.1), whereas the lowest time savings per trip are found toward the south end of the facility (Figure 4.2). Per-trip reliability savings are more evenly distributed (not unlike the pattern in Figure 2.6), but still slightly lower toward the south end of the facility. That these patterns are similar to the average toll patterns is indicative of the correlation between trip benefits and trip cost, and the overall strength of the WSDOT tolling algorithm.

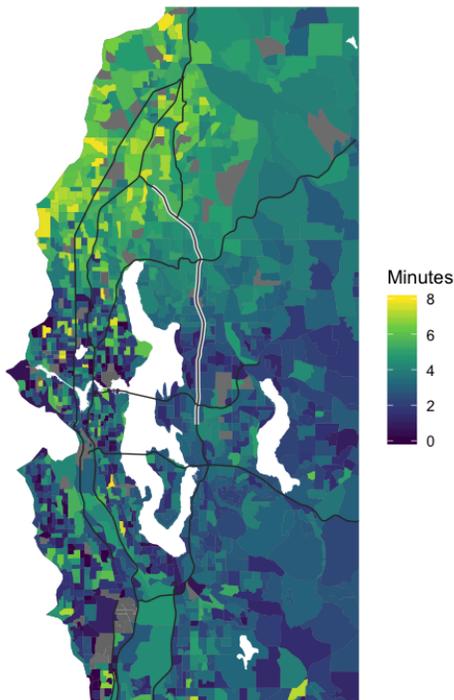


Figure 4.1. Time savings per trip, in minutes.

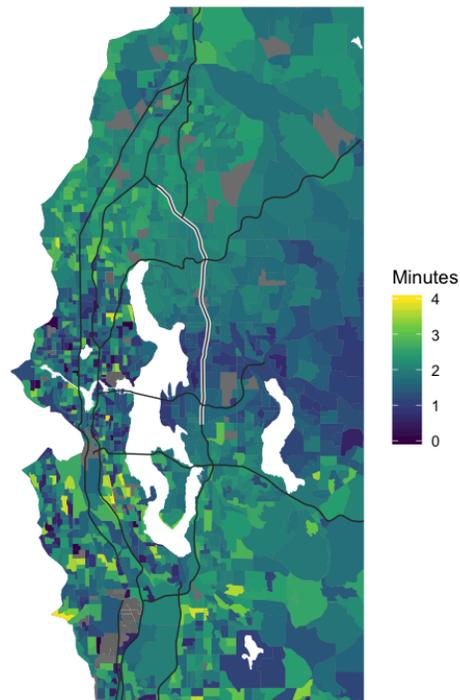
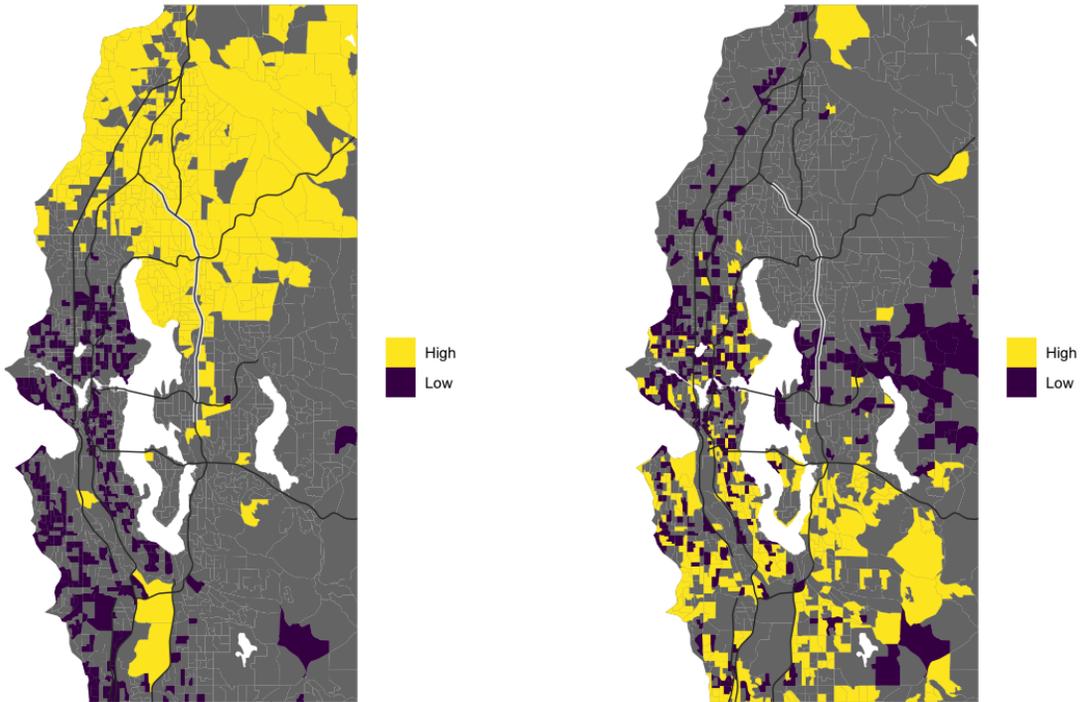


Figure 4.2. Reliability savings per trip, in minutes.

Net Benefit Per Household and Per Dollar

Figure 4.3 shows the highest and lowest quintiles of net benefit per household—which areas accumulate the most net benefit. Figure 4.4 shows the highest and lowest quintiles of total benefit per dollar spent—which areas get the best value per trip taken.



**Figure 4.3 Highest and lowest quintiles
Of net benefits per household**

**Figure 4.4 Highest and lowest quintiles
of net benefits per dollar spent**

Unsurprisingly, the highest per-household benefits are in the area around the facility where overall usage is highest. More interesting is the per-dollar distribution of benefits, which is concentrated in south King County. This pattern is probably explained by commuting patterns: commuters living south of the facility necessarily commute in the opposite direction of the usual traffic flow. In doing so, they continue to gain reliability benefits (Figure 4.2) but face lower tolls (Figure 2.5), thereby increasing their benefit-to-toll ratio.

Income Distribution

Most of the income analysis described in the usage section involved estimating the median income for a certain type of user—paying, peak commuter, high-frequency, etc. In contrast, when examining the distribution of net benefits by income, there were two possible units of analysis:

households and trips. The per-household analysis included the effects of usage: households that use the facility more (as a result of their income or location, for instance) will accrue more net benefits. The per-trip analysis ignored the effects of usage. Both have important implications for equity.

Per Household

Higher-income households accrue far more net benefit than lower-income households do, as Figure 4.5 demonstrates. The average \$200,000-per-year household in the region gains around 6.5 cents in net benefit from the facility, 86 percent higher than the 3.5 cents gained by the average household making \$50,000 per year. This pattern is almost to be expected, however, given the income differential in usage shown earlier in Figure 2.7. Households that use the facility more often naturally accrue more benefits. In fact, the same \$200,000-per-year household which takes in 86 percent more benefits than a \$50,000-per-year household uses the facility 133 percent more. This discrepancy becomes much more visible when net benefits are considered on a per-trip basis.

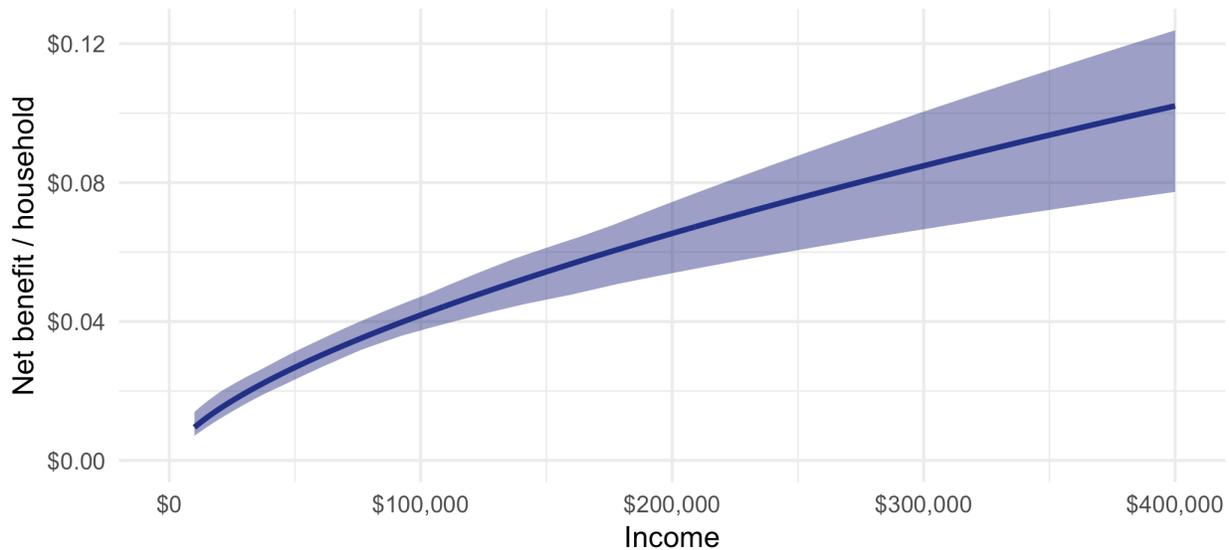


Figure 4.5. Net benefit per household by income.

Per Trip

The equity picture looks much different per trip, as illustrated in Figure 4.6. Lower-income households actually gain more net benefit per trip than do higher-income households. Returning to the same hypothetical households above, at \$200,000 and \$50,000, the former gains 21 percent *less* in net benefit per trip than does the latter. Overall, however, the distribution is quite even: nearly all drivers can expect a per-trip net of benefit between \$1.50 and \$2.50. Of course, there is substantial variation in net benefit across specific trips; the findings presented here are merely averages across a large number of users and trips.

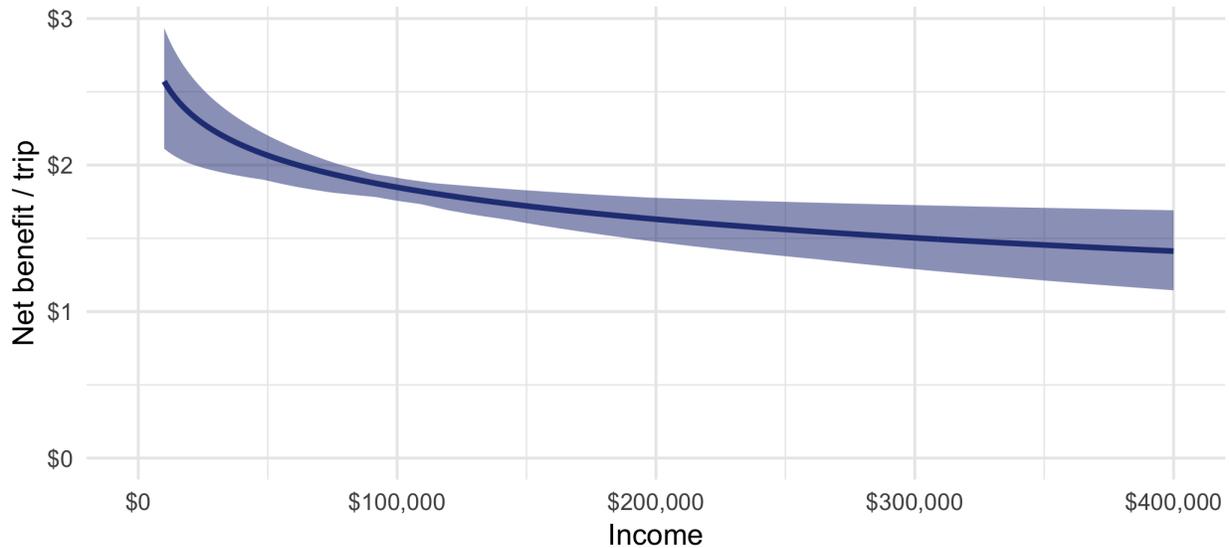


Figure 4.6. Net benefit per trip by income.

Both Figure 4.7 and Figure 4.8 show the geographic distribution of net benefit per trip. But while Figure 4.7 shows the average net benefit per trip for all users in a census block, Figure 4.8 shows the average net benefit per trip for only those users with a median household income equal to the overall median income of the travel shed.¹² This provides a hypothetical scenario in which the geographic distribution of users is the same, and all users have the same income. Figure 4.8 effectively controls for income.

Figure 4.7 shows a concentration of higher per-trip net benefit along the SR 99 corridor in Snohomish County, and south of downtown Seattle. However, these hotspots fade in Figure 4.8, in which each block group is normalized at the median income of the region, showing that the differences are primarily the result of income, not geography.

¹² \$84,200 per year.

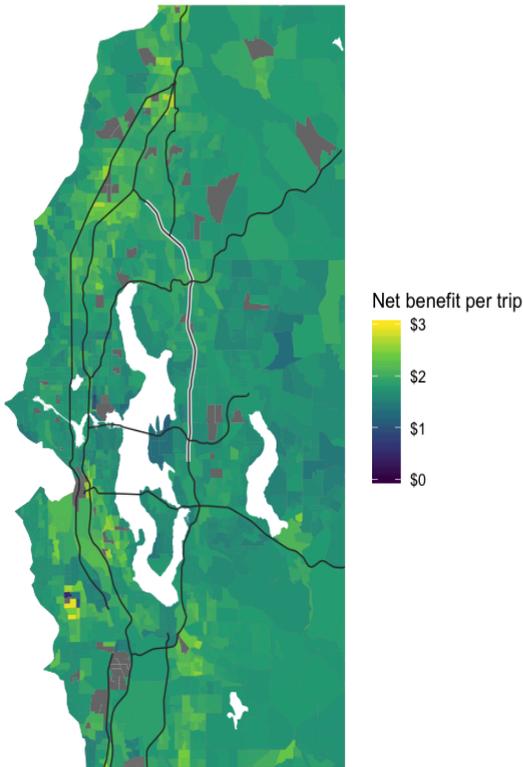


Figure 4.7. Net benefit per trip at block group income

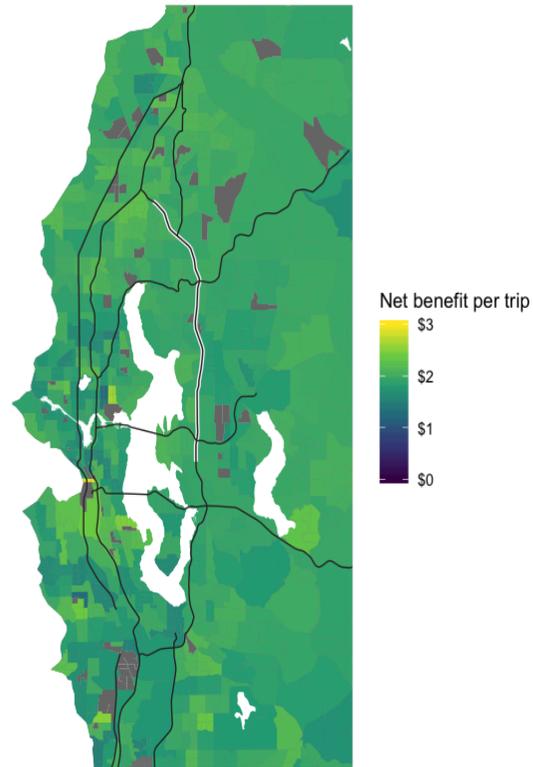


Figure 4.8. Net benefit per trip at overall Median income

Given these results, what explains the per-trip benefit-income pattern? Given the methodological challenges in estimating the benefit-income relationship in the first place, it was difficult, if not impossible, to assign a precise fraction of the blame to each variable. However, further analysis suggested that some of the pattern, but not all, can be explained by individuals' commuting patterns.

Figure 4.9 mirrors the pattern in Figure 2.9 and shows that low-income users make up a larger fraction of users during peak periods and in peak directions. Figure 4.10 shows that per-trip net benefit is highest precisely during these periods. By travelling during the periods when per-trip net benefits are highest, lower-income drivers across the region gain relative to higher-income drivers.

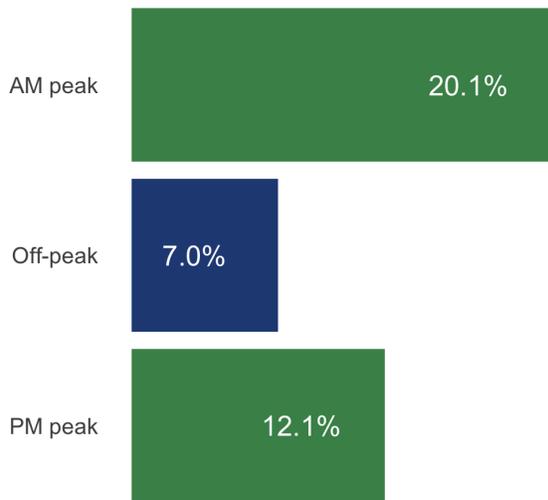


Figure 4.9 Share of users with household income below \$35,000 per year, by time of day and direction



Figure 4.10. Net benefit per trip by time of day and direction

Distribution Among Lower-Income Users

On average, lower-income users gain more net benefits per trip than higher-income users. However, among lower-income users, there is still substantial geographic variation in net benefits per trip.

Figure 4.11 shows how much more or less per-trip net benefit a low-income user within each block group (household income in the 20th percentile for the region¹³) gains in comparison to the average low-income user across the region. Average net benefit per trip is around \$2.25 for this income level, and the variation shown in the figure is a substantial fraction of this. While there is substantial variation across the region, even within small geographic areas, several general patterns emerge.

Low-income users in North Seattle gain far less net benefit per trip than their counterparts in South Seattle. Low-income users around I-5 in Snohomish County, at the north end of the facility, generally gain more net benefit per trip than do low-income users in Redmond, toward the south end of the facility.

¹³ \$36,550 per year.

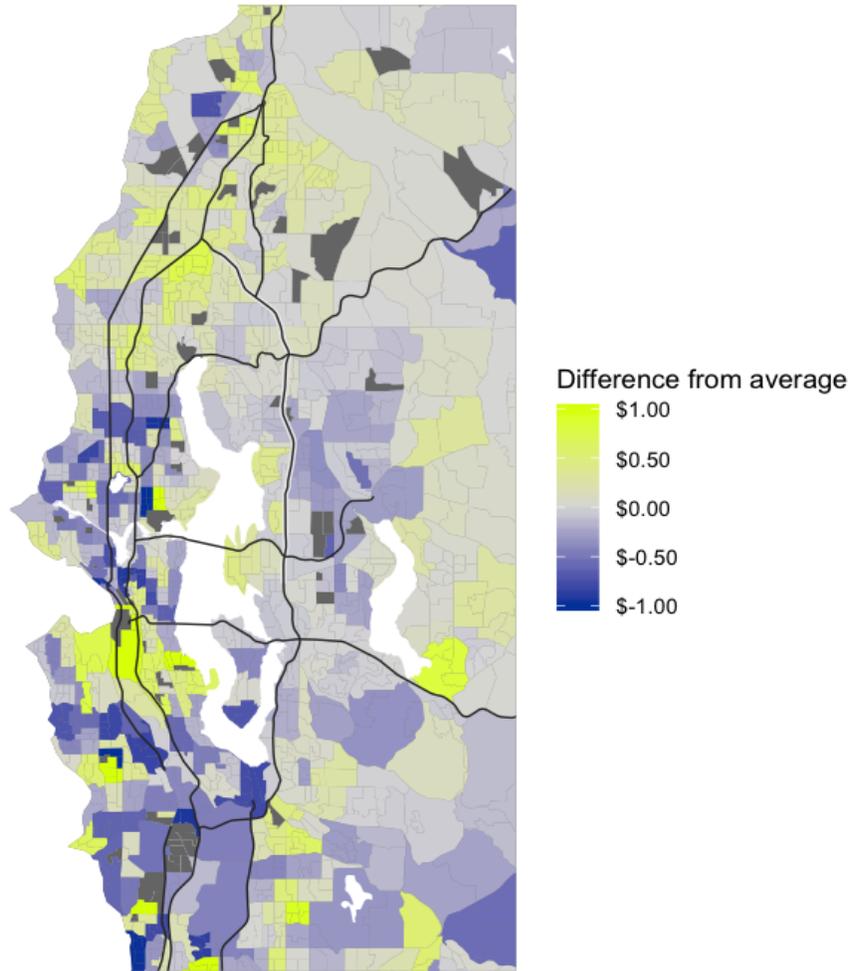


Figure 4.11. Difference from average net benefit per trip for users with a household income in the 20th percentile

Low-income users south of Renton realize less per-trip net benefit as well. It is not clear what causes these patterns, or whether they are mostly statistical artifacts, but one possible culprit is commuting patterns, and route choice in particular.

Frequency of Use Distribution

Using the frequency of use categories shown previously in Table 1.2, we examined how net benefits are distributed to frequent versus infrequent users of the facility. Figure 4.12 shows the percentage of trips made by each frequency group during peak periods. The distribution of net benefits is shown in Figure 4.13. Naturally, higher-frequency users accumulate more net benefit than lower-frequency users, but even making comparisons on a per-trip basis, the pattern persists: daily users gain nearly double the net benefit per trip than one-time users.

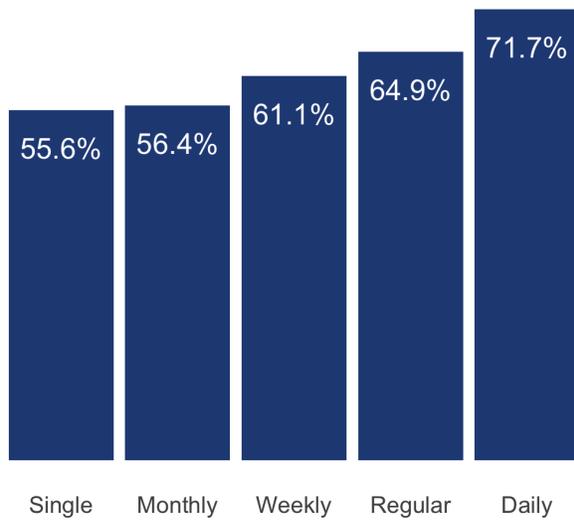


Figure 4.12 Percentage of trips during peak periods by frequency of use.

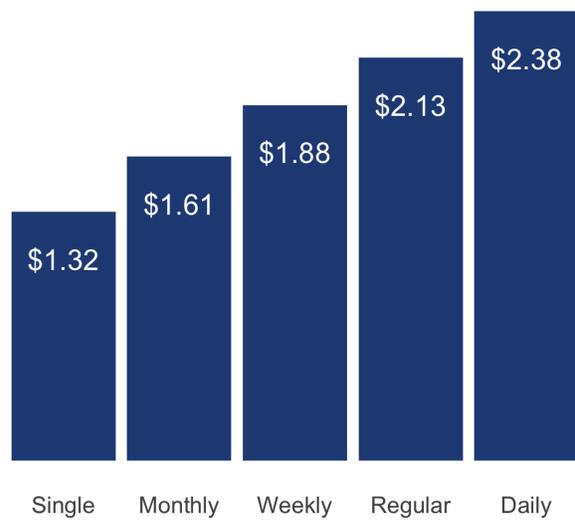


Figure 4.13. Net benefit per trip by Frequency of use

As with the per-trip benefit-income pattern, this benefit-frequency pattern can be at least partially explained by users’ choices to drive during peak periods, and the trend is remarkably similar to that seen in Figure 4.12: daily users travel mostly during peak periods and, therefore, accrue more net benefit than one-time users, who are nearly evenly split between peak and off-peak periods.

Route Distribution

Figures 4.7 and 4.8, shown previously, suggest that geography explains little of the per-trip benefit-income pattern. That is not to say that geography is unimportant, however. Figure 4.14 (similar in construction to figures 2.17–2.19) shows how net benefits per trip vary widely by route choice and time of day. Squares in the figure are sized proportionally to the absolute value of net benefit and are colored by whether the benefit is negative or positive. Off-peak trips are not shown, as trip volumes were lower and the patterns were similar to the peak patterns.

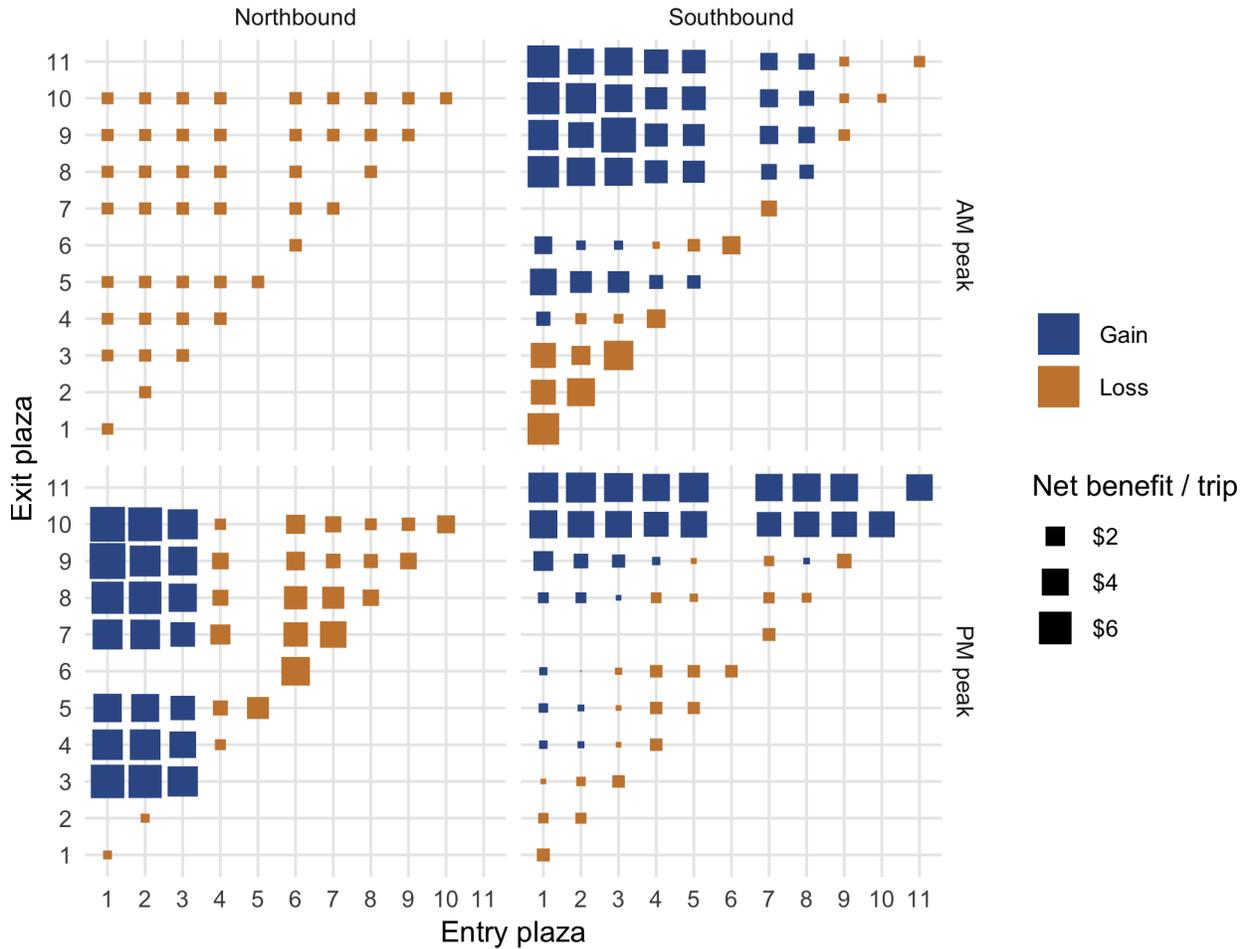


Figure 4.14. Net benefit per trip by route and time of day.

The patterns in Figure 4.14 by entry and exit are striking. Morning northbound users have a negative net benefit for all routes, which is to be expected, given the lack of congestion on those routes. Northbound afternoon routes that begin south of Kirkland gain on average, while routes beginning north of Kirkland lose on average. Southbound morning routes that end south of SR 522 and southbound afternoon routes that end in Bellevue (where afternoon traffic is concentrated) gain on average, while other southbound routes lose on average. The highest losses are for northbound users traveling from the NE 128th DAR to SR 522, and southbound users travelling the first segment of the facility, by Lynnwood.

Conclusions

On a highway facility as large as the I-405 express toll lanes, carrying millions of vehicles a year, the question of equity is far from simple. Equity can be measured in multiple ways, and each method gives a slightly different answer.

A key aspect of the HOT lanes, which is not found in several other congestion pricing schemes, is that drivers have complete choice of whether to pay the toll. Congestion in the general purpose lanes has, if anything, improved slightly since the facility opened in 2015,¹⁴ so drivers who elect not to pay a toll are not losing anything per trip. In comparison to a system in which all drivers are forced to pay a toll, this mitigates concerns about equity; we need not be concerned that certain groups are being entirely priced out of driving—only that they could be unable to reap the benefits of the facility.

Higher-income households use the facility at a higher rate (Figure 1.7). This leads to an unequal distribution of facility benefits: higher-income households accrue more benefit per year (Figure 3.5). In this regard, congestion-free travel is like any other economic good: those with higher incomes can afford to consume more.

But despite the overall income-usage trend, many drivers across the income spectrum use the facility at least once. In fact, this one-time user group is broadly representative of the region's income distribution, and even skews toward lower incomes (Figure 1.12 and 1.13). Furthermore, a strong majority of these one-time users pay through their license plate, suggesting that these trips are taken on an ad-hoc basis when users most need the time savings.

And when net benefits are examined on a per-trip basis, they are distributed relatively evenly, but on average they accrue slightly more to lower-income drivers (Figure 3.6). Thus, although higher-income drivers use the facility more overall, they are not using it as efficiently as lower-income drivers. When lower-income drivers need to make trips on the facility, they gain the most.

This pattern is difficult to fully explain, but route choice (Figure 3.14) and commuting patterns (figures 3.9 and 3.10) contribute in part. The fact that net benefit per trip is strongly influenced by these temporal and geographic factors, and that toll rate determination may vary by these same factors, gives WSDOT the flexibility to address issues of equity and system performance and to target policies to certain groups of users. Some of these policies are examined in the next section.

¹⁴ *I-405 Express Toll Lanes: 39 Months of Operations* (Olympia: Washington State Department of Transportation, 2018), 5.

Chapter 5: Policy Analysis

Without the ability to perform experiments on the facility, policy analysis is necessarily counterfactual, and therefore complicated by untestable assumptions, unobserved factors, and feedback effects. Despite these challenges, we analyzed two potential toll policy changes and their impacts on revenue, volume, and equity. We caution that these results are preliminary and serve only as first-pass approximations of policy change impacts.

Raising the Minimum Toll

Figure 2.9 shows that higher-income drivers disproportionately use the facility during off-peak hours. During these off-peak hours, the toll is usually at the minimum value of \$0.75 for long periods of time. It is therefore possible that by raising the minimum toll from \$0.75, additional revenue could be generated without leading to an excessive impact on equity. Moreover, as higher-income users are distributed more toward the south end of the facility, the minimum toll could possibly be raised selectively for certain segments, further minimizing the equity impact. We examined this policy in detail and found that revenue could be increased substantially, with minimal impacts on equity and moderate impacts on total volume.

Methodology

For each policy option, we generated a copy of the trips data set and raised the toll for each trip below the new minimum toll. We also randomly removed trips whose tolls were raised in proportion with the price elasticity shown in Table 2.1 (but adjusted for the lower toll level)¹⁵ to account for the lower volume of trips made in response to the higher toll. We then recalculated total revenue and volume across the year, and re-estimated the relationship between net benefit per trip and income. If the relationship strengthened (i.e., lower-income users benefited even more per trip), we classified this as an equity improvement. Conversely, we classified a weakening in the relationship as a worsening of equity.

Facility-Wide Change in the Minimum Toll

Table 5.1 shows the estimated impacts of raising the minimum toll to \$1.00 and \$1.25 across the facility. Unsurprisingly, a higher toll minimum leads to increased revenue and decreased volume. But a higher minimum toll also has a positive equity impact, as net benefits per trip are distributed more in favor of lower-income users.

¹⁵ After adjustment, the price elasticity used was -0.3394 .

Table 5.1. Estimated impacts of raising the minimum toll.

Minimum Toll	Revenue Change	Volume Change	Equity Change ¹⁶
\$1.00	8.9%	-6.0%	6.9%
\$1.25	18.3%	-12.2%	15.8%

Selective Change in the Minimum Toll

Toll minimums could also be raised for only certain routes. As the primary direction of travel is southbound in the morning and northbound in the evening, raising the minimum toll for southbound trips originating past a certain entry point, and northbound trips ending before a certain exit point, would align toll rates most closely with the geographic distribution of income.

We examined all possible combinations of entry and exit points past which to apply the higher minimum toll. The most promising combinations for each possible level of toll are presented in Table 5.2.

Table 5.2. Estimated impacts of raising the minimum toll.

Minimum toll	Southbound trips starting after	Northbound trips ending before	Revenue change	Volume change	Equity change
\$1.00	(all SB trips)	3 (NE 70th)	1.0%	-0.7%	19.5%
\$1.25	9 (NE 70th)	4 (NE 160th)	5.0%	-3.7%	11.8%
\$1.50	5 (NE 160th)	5 (NE 128th DAR)	12.8%	-9.4%	38.5%

Raising the Maximum Toll

Raising the toll cap from \$10 is promising not only because of potential revenue generation, but because it could substantially increase facility performance. However, it is precisely this benefit that makes analyzing the impacts of a change in the maximum toll more complicated. Were a higher toll cap to increase facility performance, it would also increase demand for the facility. Furthermore, counterfactual analysis was complicated by the inability to know exactly what the

¹⁶ Equity change was calculated as the percentage change in the income elasticity of net benefit per trip (the slope of the line in Figure 4.6) from the \$0.75-minimum regime to the alternate regime.

toll would be without the toll cap in place. We attempted to address the latter issue but were unable to model the increase in demand as a result of a better-functioning facility.

Methodology

Estimating the impact of a raise in the toll cap required assigning each trip a new toll and then accounting for changes in time savings and overall volume.

For trips paying the maximum toll of \$10.00, we estimated a new toll by increasing the toll in proportion to the difference between the local HOT lane speed and 60 mph, with the maximum toll kicking in when HOT lane speed reached 45 mph. So for a hypothetical toll cap of \$16, a \$10 trip with a local HOT lane speed of 60 mph would still be \$10, but if the lane speed were 50 mph or 30 mph, the toll would be \$14 and \$16, respectively. Tolls below \$10 were not altered, consistent with the assumption that WSDOT would raise tolls above \$10 only to manage traffic and would not use a higher toll cap to inflate all tolls proportionally.

To estimate new time savings, we increased the actual time savings in proportion to the ratio between the local HOT lane speed and 45 mph. So if a trip's actual HOT lane speed were 30 mph, and the user saved 6 minutes, we estimated a new savings of 9 minutes. If the trip's HOT lane speed was above 45 mph, no time savings adjustment was made. Volume adjustments were made as above—trips were randomly dropped according to a set price elasticity. Different revenue impacts were found depending on the overall elasticity.

Moderate Price Sensitivity

If users paying the maximum tolls are on average as price sensitive as users overall (a price elasticity of -0.64), then raising the maximum toll will increase overall revenue—to a point. Revenue would be maximized at a toll cap of \$15.00. Table 5.3 shows estimated changes in volume, revenue, and equity for different toll caps. Equity estimates are conservative, as we assumed a constant price sensitivity across incomes, while in reality lower-income households are likely to be more price sensitive. Equity impact estimates should therefore be considered lower bounds. The estimates, however, suggest that equity is barely affected until the toll cap exceeds \$15.00.

Table 5.3. Estimated impacts of raising the maximum toll, assuming a price elasticity of -0.64 .

Maximum Toll	Revenue Change	Volume Change	Approx. Equity Change
\$11.00	0.4%	-0.1%	-1%
\$12.00	0.6%	-0.2%	-1%
\$13.00	0.7%	-0.4%	-1%
\$14.00	0.8%	-0.5%	-1%
\$15.00	0.9%	-0.6%	-2%
\$16.00	0.7%	-0.8%	-3%
\$18.00	0.2%	-0.9%	-3%

Higher Price Sensitivity

If users paying the maximum tolls are more price sensitive than users overall (a price elasticity below -1), then raising the maximum toll will only decrease revenue and will have a stronger effect on volume. Table 4.4 shows estimated changes in volume and revenue for different toll caps, assuming an elasticity of -1.2 . Equity is impacted slightly more than above, but the effects are still quite small, and not enough to reverse the progressive distribution of per-trip benefits.

Table 5.4. Estimated impacts of raising the maximum toll, assuming a price elasticity of -1.2 .

Maximum Toll	Revenue Change	Volume Change	Approx. Equity Change
\$11.00	0.0%	-0.2%	-2%
\$12.00	-0.2%	-0.5%	-2%
\$13.00	-0.6%	-0.7%	-2%
\$14.00	-1.1%	-1.0%	-2%
\$15.00	-1.9%	-1.2%	-3%
\$16.00	-2.7%	-1.4%	-4%
\$18.00	-5.0%	-1.9%	-4%

Appendix A: Data Statistics and Quality

Trip Data

WSDOT recorded over 56 million toll plaza transactions in 2018, corresponding to 16,976,134 individual trips. Most, but not all, of these trips could be linked to a unique user identifier, based on either the user's license plate or their online account. Some of these plates and accounts could be linked to the census block at which the user was registered. Table A.1 describes the fraction of users in each category. SOVs accounted for 71 percent of trips, 29 percent were HOV.

Table A.1. Data quality summary statistics.

	Fraction of SOV Trips	Fraction of HOV Trips
Census and account information	57%	74%
Account or plate information only	26%	—
No identifying information	16%	26%

There were 828,983 identifiable users, 3,200 of which were classified as commercial users. In 2018, noncommercial users made 14.5 trips on average, while commercial users made 566.5 trips on average.

Census Data

Each HOT lane user account or license plate was associated with a census block group presumably corresponding to the driver's residence. We used the 2016 5-year American Community Survey (ACS) census data to get information about income, race, and transportation mode for each of the 3,100 block groups in our nine-county region: King, Kitsap, Kittitas, Pierce, Skagit, Snohomish, Thurston, Whatcom, and Yakima.

Appendix B: Income Methodology

Most graphics in the report are the result of an aggregation and computation of summary statistics. However, use of American Community Survey (ACS) data at the block group level, rather than individual income and demographic information, created several methodological challenges that necessitated a more complex modeling approach.

Fitting Distributions to Income Histograms

The ACS reports, for each census block group, the fraction of households within a series of income bins (\$0–\$35,000, \$35,000–\$50,000, etc.). To estimate income quantiles, and to be able to simulate incomes from each block group, a distribution must be fit to the income bin percentages.

The two-parameter Weibull distribution and the three-parameter Dagum distribution have been widely used to describe the distribution of income in the developed world. Both are supported on the nonnegative reals and have one or more shape parameters that control the variance, skewness, and kurtosis of the distribution.

We can fit these distributions to the data by recognizing that for a chosen distribution and fixed set of parameters, the cumulative distribution function predicts the fraction of households that should fall within each income bin. Given a set of households—in a census block group or across the region—we can model the likelihood of assignment to income bins as multinomial. Minimizing the negative log-likelihood across the parameter space for the distribution then yields a best-fit distribution for the observed income bin counts. With the fitted distribution in hand, it is easy to estimate means and quantiles, as both the Weibull and Dagum distributions have closed-form expressions for these quantities. The inverse negative Hessian from the log-likelihood maximization gives the estimated covariance matrix of the parameters, which can be used to form uncertainty intervals around these same quantities of interest.

Estimating How Quantities of Interest Vary by Income

Without individual-level income information, we cannot with full certainty generate the distribution of quantities of interest across income levels. We must instead make assumptions about how individuals within and across census blocks use the HOT facility, and use these to estimate the overall distribution of income.

Bad Assumption: Usage Is Independent of Income, Given a Neighborhood

If we assumed that HOT facility usage was entirely explained by where one lives, we could simply average the income bin fractions (see above) across census block groups, weighted by the number of trips (or users) originating from that block group. This would yield an overall income histogram, to which a parametric or semiparametric distribution could be fitted. Unfortunately, this assumption is not plausible on its face—we expect usage patterns to vary strongly by

individual income, regardless of geography.

Better Assumption: Usage Is Independent of a Neighborhood's Income, Given Neighborhood Location and Individual Income

This assumption is more nuanced, but much more plausible. Given an individual's income, and the census *tract* they live in (census tracts generally contain between two and five block groups), we would not expect the individual's usage to vary depending on the overall level of income in their block group. For instance, take two individuals, Bob and Jane, who live in adjacent block groups in the same census tract. Both make \$50,000 per year. Bob's block group is wealthier than Jane's block group. Without knowing any more information (such as where Bob and Jane work), we have no reason to believe that Bob or Jane is more likely to use the facility—they make the same amount and live in the same area.

With this assumption, we could regress usage on income (usually on a log-log scale), with each observation a block group (rather than an individual). Letting the intercept and slope vary by census tract, we could interpret the resulting fixed effect coefficients as the coefficients we would have estimated if we had regressed on individual income instead. Assuming a log-log specification, these estimates might be directly interpreted as elasticities of usage with respect to income. Figures such as Figure 1.7 were generated this way. Alternatively, the estimates would allow us to simulate incomes from the overall population distribution (itself fit using one of the methods detailed above), then use the model to predict usage for each simulated individual. From this synthetic population, quantities of interest were easily calculated.

Appendix C: Modeling HOT Usage

We used a linear regression model to describe the relationship between our variables of interest. The estimating equation follows:

$$y_{ijt} = \beta \text{Toll}_{ijt} + \alpha \text{GPspeed}_{it} + \eta \text{GPvolume}_{it} + \varphi \text{EstTimeSaving}_{ijt} + \lambda \text{Reliability}_{ijt} + \theta \text{TripLength}_{ij} + u_{it}$$

where y_{ijt} is the count of SOVs that enter at time t and gate i and are heading to gate j , and u_{ijt} is the error term. To obtain estimates for VOT and VOR, we calculate $-(\varphi / \beta)$ and $-(\lambda / \beta)$ to find the rate of substitution between time/reliability and money, as described in the modeling section.

Price elasticity can then be calculated by using the ratio of average value of toll and average volume multiplied β , and can also be calculated by using averages at different subsets of data (northbound versus southbound, and peak versus off-peak). Elasticities by time of day can be found in Figure 2.3 where elasticity measures vary from -0.30 off peak to -1.29 southbound during the morning peak.