

# Parking Management Scenario Planning for the Port Authority of Allegheny County

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## 1. Executive Summary

### 1.1 Background

Park and Ride (PnR) facilities are public parking lots that offer a convenient location for commuters to leave their vehicles while transferring to a public transit line to reach their final destination. The Port Authority of Allegheny County (PAAC) transit system contains over 50 PnRs with over 13,000 parking spaces. Currently, all but two of the PAAC-owned lots offer parking free-of-charge to their users. Because the lots have significant, ongoing, maintenance and capital costs totaling approximately \$4 million annually, this results in a net revenue loss for the PAAC. An ongoing question for the PAAC is whether owning and operating PnRs is the best use of that money, or if the communities of Allegheny County could be better served if PnRs were fee-based and parking revenue was used to expand services elsewhere. The goal of this project is to explore how the PAAC can grow and diversify its revenue streams primarily through leveraging PnR facilities while also maximizing ridership and reducing single-occupancy vehicle miles travelled. Furthermore, any solution should avoid disproportionately burdening low-income or other disadvantaged communities.

A challenge the PAAC faces in solving this problem is a limited understanding of the demand for PnRs and the price sensitivity of their users. The PAAC would not be able to achieve its revenue goals if implementing a parking fee dramatically reduces PnR utilization, and that uncertainty is a main source of hesitation for implementing fees at their lots. Therefore, understanding commuter behavior, prioritization, and decision making is essential to answering our question and is thus the focus of the model we built.

### 1.2 Model Choice and Formulation

In order to better understand how features of transportation modes such as cost, commute time, and reliability are prioritized by commuters when making decisions about which mode to use for commuting, we built a Mode Choice Model (multinomial logit). This modeling technique is well documented in the literature for understanding commuter priorities and making predictions about commuter responses to potential

changes in costs or service offerings. Due to time limitations, we focused our model on commuters East of Pittsburgh who commute during morning rush hour to either downtown Pittsburgh or Oakland. For these commuters, we considered three possible modes of transportation: driving, taking the bus, or driving to one of the three PnRs on the East Busway (Wilkinsburg, Hamnett, or Swissvale) and then taking the bus. Make My Trip Count (MMTC) data, a survey of Pittsburgh area commuters conducted in 2018, was used to get information about a sample of commuters and estimate the prior probabilities for utilizing each mode of transportation. Then data on the total cost, total transit time, and overall reliability was collected for each mode of transit. This data combined with income data from the MMTC dataset was used to create our multinomial logit model.

### **1.3 Model Results and Interpretation**

The key results from our model are:

A \$2 daily parking fee charged at PnRs on the East Busway would reduce PnR demand by approximately 23%

As the distance between the origin and destination increases, the commuters are more likely to choose driving over other modes

Given that the average utilization in 2019 across all three lots was 1,009 cars, a 23% decrease would represent a loss of approximately 232 users daily. Importantly, as parking at each lot is limited, it is impossible to tell if demand for parking at these lots actually exceeds the capacity of the lots. If that is the case, then it is possible that the decrease in PnR utilization would be significantly less than is predicted by our model.

Two limitations of the model are that the MMTC dataset is not a random sample of Pittsburgh area commuters and thus may not accurately reflect the prior probabilities of using each mode of transportation, and that all travel time data was collected during the COVID-19 pandemic and thus likely underestimates the travel time experienced by those filling out the MMTC survey.

## **1.4 Recommendations and Project Impact**

One of our deliverables for this project is an editable Excel sheet which allows the user to change various assumptions (such as the annual cost of implementing charged parking and the parking fee that would be implemented) and in turn gives readily interpretable estimates of expected changes in annual revenue. We anticipate that this data will be useful to the PAAC when considering the tradeoffs of charged parking implementation. Future work could include expanding the model we created to also focus on PnRs to the South and West of Pittsburgh and compare the price sensitivity of commuters in different parts of the city. The model could be improved in future iterations by obtaining information about whether commuters have access to a car, a question that was not addressed in the 2018 MMTC survey. Ultimately, we hope that our findings will be informative to PAAC as they consider next steps for diversifying their revenue streams.

## 2. Project Objectives

The Port Authority of Allegheny County (PAAC) provides approximately 64 million rides each year to the Allegheny County area. In addition to traditional metropolitan transit services such as bus and light rail lines, the PAAC also owns and operates 25 of the 50 park and ride (PnR) lots within its system; these 25 lots contain roughly 8,290 spaces. All but two of these lots offer parking spaces free of charge, but the cost of maintaining and operating these lots is approximately \$4 million annually. An ongoing question for the PAAC is whether owning and operating PnRs is the best use of that money, or if the communities of Allegheny County could be better served if PnRs were fee-based and those funds were used to expand services elsewhere.

The COVID-19 pandemic has had an immeasurable impact on economic activity around the world. In Allegheny County, transit ridership has fallen 70%, and it remains unclear when ridership will return to its pre-pandemic levels. With revenues down, the question of how to diversify revenue streams or lower operating costs becomes even more important.

The goal of this project is to help the PAAC explore options for diversifying revenue and maximizing the value of the parking system. This includes increasing revenue in a way that does not disproportionately burden low-income or minority race communities and minimizing the long-term maintenance and capital costs associated with the PnR lots. Secondary goals include maximizing ridership and reducing single-occupancy vehicle use and vehicle miles traveled.

When determining whether a fee based PnR system is worthwhile, understanding how PnR users may respond to price changes is critical for forecasting potential revenue. This is the essential question our project attempts to address in the context of Allegheny County. In this report, we examine the literature on PnR demand and fees and look at PnR utilization and demographics in Allegheny County. We then construct a model to help predict PnR user behavior in Allegheny County for a subset of PnR lots situated on the East Busway.

### 3. Literature Review

#### 3.1 Park and Ride Finances

The Port Authority of Allegheny County operates a massive public transit system in Western Pennsylvania with over 7,000 bus stops, 27 light rail stations, two inclines, and additional services for the elderly and people with disabilities (Port Authority of Allegheny County, 2021). Their annual operating budget is over \$400 million per year, and almost 1% of that budget (\$4 million per year) goes towards the upkeep and maintenance of the 25 PnR lots owned and operated by PAAC (Port Authority of Allegheny County, 2021). Notably, the cost per passenger ride has increased in recent years and the average revenue received per ride covers only a small portion of the total cost (Port Authority of Allegheny County, 2018). The remaining cost is covered by subsidies from federal, state, and local funding sources (Port Authority of Allegheny County, 2018).

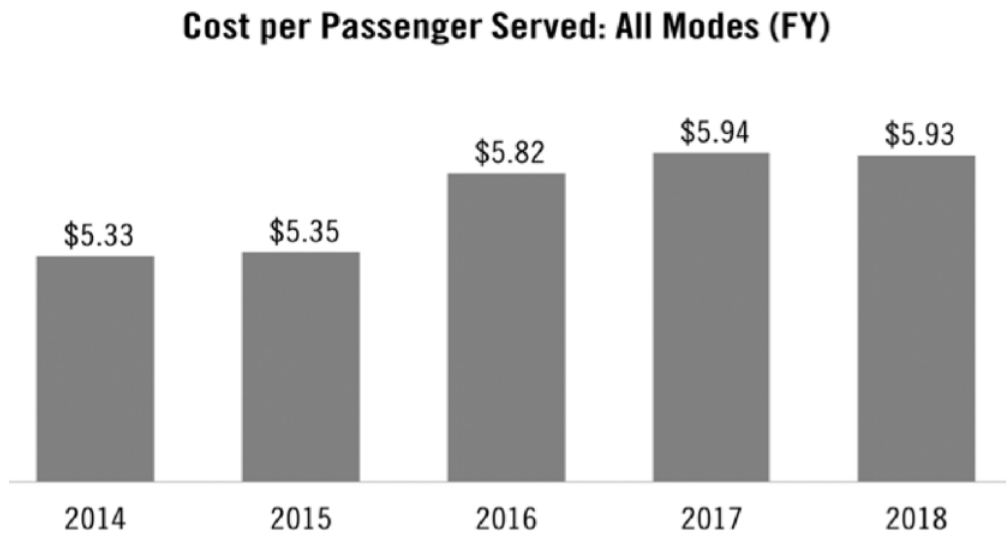


Figure 1: Cost of operating the Allegheny County transit system per passenger served as reported in the 2018 PAAC Annual Service Report

When considering the potential value of implementing a charged parking system at these lots, it is important to understand how much potential revenue and additional costs such a system is likely to incur. In the most optimistic calculations implementing a charged parking system requires no annual costs and has no impact on PnR utilization. In that scenario, using utilization rates from 2019, implementing a \$2 per day parking fee at all

PAAC-owned PnRs could bring in an additional \$2.5 million in annual revenue (Port Authority of Allegheny County, 2019-2020). Notably, this optimistic revenue calculation does not cover the annual costs of PnR maintenance. In fact, a review of transit organization parking revenue and expenses in cities across the U.S. shows that PnR charged parking systems never cover the cost of operation (National Academies of Sciences, Engineering, and Medicine, 2016). Even in extremely dense, wealthy cities where snowfall does not contribute to additional expenses such as Washington D.C. and San Francisco, charged parking only covers a maximum of 66% of all PnR related expenses (National Academies of Sciences, Engineering, and Medicine, 2016). More data on this can be found in Table 1 of the Appendix.

While explorations of the relationship between transit fares, cost of parking, and transit ridership are largely missing from the literature, there is some evidence that in cases where parking lots are more than 90% utilized, increasing the parking price does not have an impact on occupancy rates even if it may result in a shift in users (National Academies of Sciences, Engineering, and Medicine, 2016). This is likely due to the fact that there is latent demand for parking lots which are consistently full, so implementing charged parking does reduce demand, but not enough for the demand to fall lower than the supply. This contrasts with what has been observed in underutilized parking lots where implementing charged parking causes a significant reduction in utilization (National Academies of Sciences, Engineering, and Medicine, 2016).

Given this relationship between utilization rates and the utilization impacts of charged parking, it is important to consider the impact that COVID has had on PnR utilization. Analysis of PAAC PnR utilization data showed that in 2019, 16 of the 25 PAAC-owned PnRs had average utilization rates over 90%. Since the pandemic began, average utilization has fallen from 83% to 13% and there are currently no PAAC-owned PnRs operating at over 90% utilization. Because of this drop, PAAC would be well-advised to wait until transit and lot-utilization numbers increase close to their pre-pandemic levels before considering implementing any sort of charged parking.



We also wanted to investigate whether cities comparable to Pittsburgh had PnRs as part of their transit systems and whether they implemented charged parking or offered parking free of charge. We used the transit systems that PAAC typically uses as comparison systems,<sup>1</sup> but we also included Portland and Vancouver as advised by our contact at PAAC. Figure 2 shows that Pittsburgh has lower ridership numbers than most of these comparison cities. While that is true, we also found that Pittsburgh has one of the highest bus fares relative to comparable cities (Figure 3).<sup>2</sup>

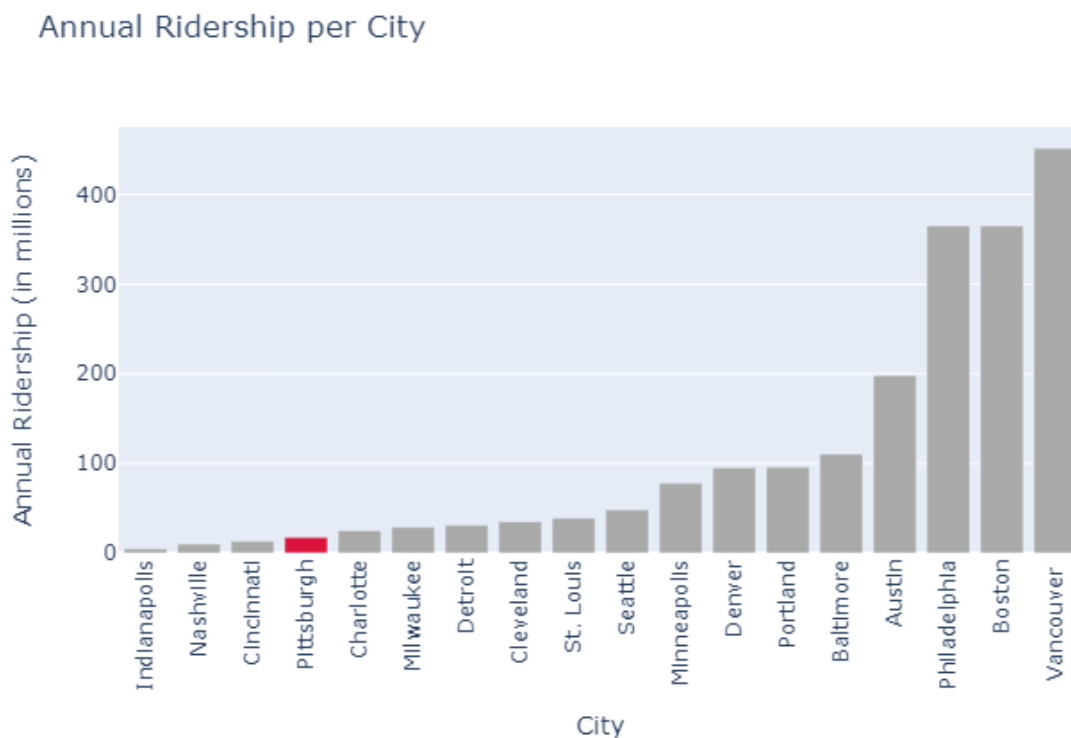


Figure 2: Bar chart showing the relative annual ridership levels of Pittsburgh area public transit and that of its comparison cities. Pittsburgh has been highlighted in red for visual convenience.

Among these cities, charged parking was rare with only five other cities using any form of charged parking.<sup>3</sup> Those that did charge for parking tended to charge low rates (less than \$2 per day) and only charged at particular lots. The exception to this rule is Boston which

<sup>1</sup> Benchmark Cities as defined by Pittsburgh Quarterly: Boston, Seattle, Philadelphia, Baltimore, Denver, Minneapolis, Milwaukee, Cleveland, Austin, Charlotte, St. Louis, Cincinnati, Detroit, Indianapolis, and Nashville. <https://pittsburghquarterly.com/indicators/transit-usage/transportation/unlinked-passenger-trips-per-capita/>

<sup>2</sup> The data for these figure was compiled by one of our team members by collecting data from the transit websites for each relevant metro area.

<sup>3</sup> Boston, Philadelphia, Cleveland, Seattle and Vancouver

typically charges \$2-15 per day at all its PnRs. A more detailed look at the charged parking rates for Pittsburgh’s comparison cities is included in Table 2 in the Appendix.

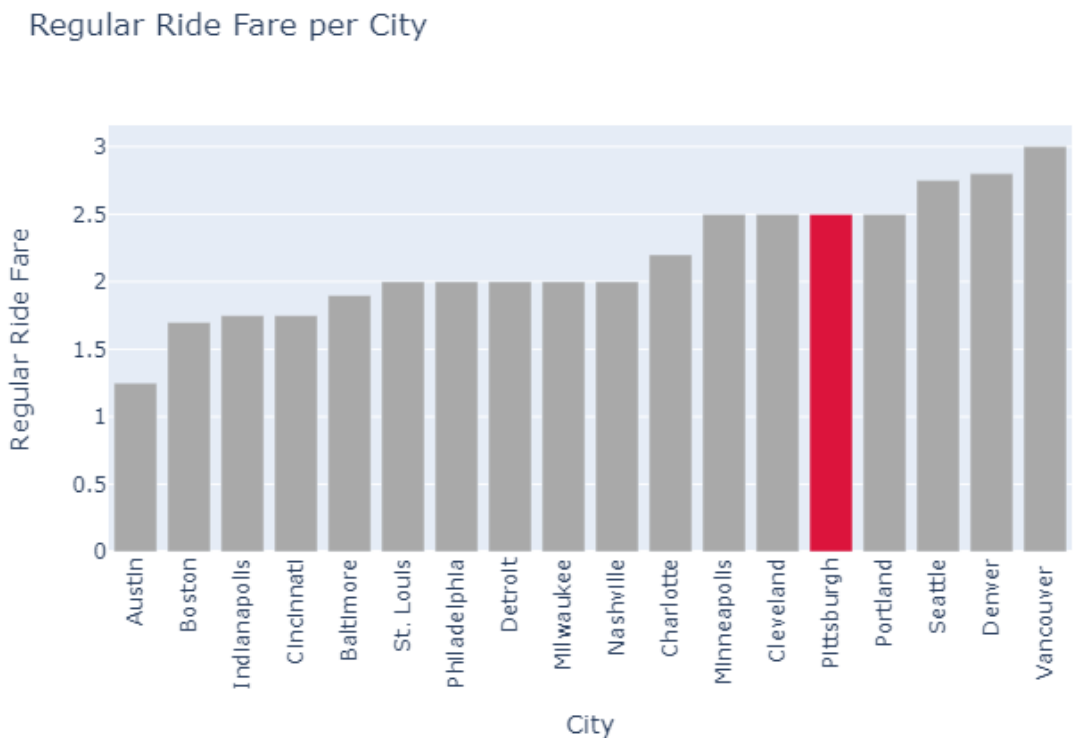


Figure 3: Bar chart showing the relative bus fare of Pittsburgh area public transit and that of its comparison cities.

Another important factor to acknowledge when considering implementing charged parking is how doing so might impact disadvantaged communities. As shown in Table 1, a cursory look at statistics related to PnR users gives the impression that they are better off financially and in terms of their education level on average than Allegheny county residents.

Such a simplistic comparison, however, does not acknowledge the relatively rare PnR user who would find a parking fee burdensome. Based on the 2019 PAAC Rider Survey, 11% of PnR users earn less than \$35,000 per year. One way to address equity concerns would be to consider different modes and methods of offering charged parking. For example, if charged parking were implemented such that PnR users could pay with their ConnectCards, then individuals who are eligible for transit discounts could receive parking discounts as well.

Metric	Allegheny County (U.S. Census Bureau (2019), 2021)	PnR Users (Port Authority of Allegheny County, 2019)
Have a Bachelor’s Degree or Higher	42%	87%
Are a Homeowner	64%	74%
Non-Hispanic, White	78%	88%
Median Income <sup>4</sup>	\$59k	\$75k - \$99k

*Table 1: Table comparing statistics related to economic wellbeing for Allegheny County as a whole and PnR users in Allegheny County. On every metric, PnR users are better off on average than residents of Allegheny County.*

### 3.2 Approaches to Charged Parking

Upon reading about the parking management systems in different cities, we learned that there are mostly three approaches to implementing parking fees in PnRs - Paid Reserved Parking, Fixed Parking Fee for Everyone, and Dynamic Pricing.

*Paid Reserved Parking:* In this setup, some spaces can be reserved for commuters who have ConnectCards or have already paid for parking online on a dedicated web platform. In some counties (for e.g., King County, Washington) only certain spaces are available to reserve, the remaining are left to be filled on a first come first serve basis (SoundTransit, 2021). One of the benefits of doing this is that it can be marketed among commuters as a special amenity as they will not have to worry about getting to the parking lot early to find a vacant space. This is also considered to be an equitable solution as the commuters who can afford to pay for the parking would pay to reserve their spaces, while still leaving some spaces for the others who may not be able to afford the parking fee. However, this approach only makes sense in parking lots with very high utilization rates where people may be concerned about not being able to get a space and thus be willing to pay to reserve one. Furthermore, reserved parking systems limit the total possible revenue that can be obtained from a lot as only a fraction of the spaces become paid spaces. Another drawback

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<sup>4</sup> Median income is measured at the household level in the Census and at the individual level for PnR users, so this disparity is even larger than it appears. The median income for PnR users could not be measured precisely because the survey had users select income brackets.

to this method is that enforcement costs are high as you must have some way to prevent people from parking in reserved spaces if they have not reserved them.

*Fixed Parking Fee for Everyone:* Under this approach, a fixed parking fee is charged to everyone who parks their car at PnRs. As compared to the Paid Reserved Parking setup, not much investment is required as the honor system can be used for enforcement and fee collection. On the other hand, such a system may result in a drop in the lot utilization rate, which can also lead to reduction in bus ridership and higher cases of Hide & Ride (cases when instead of parking at PNRs, people choose to park their cars in nearby residential areas and commercial complexes).

*Dynamic pricing:* In Dynamic pricing, the parking fee can be varied from being free to some amount depending on the demand and supply of parking spaces at a PnR. The supply is always fixed as there are a limited number of parking spaces in any given lot, and demand is monitored digitally as lots begin to fill. For this system to work in real-time, granular data must be readily available. The objective of this approach is to make revenue while maintaining high utilization of the parking lots.

### **3.3 Parking Fee Collection Technologies**

We researched different parking fee collection technologies that are available for Port Authority if they plan to implement paid parking at PnRs. While some of the technologies fit better in a reserved parking setup, the others are well suited to the other setups as discussed in the previous section. The technologies we focused on broadly belong to five categories - Digital Single Space Meters, Digital Multi Space Meters, Pay by Phone, Radio Frequency Identification (RFID), and Automatic License Plate Recognition (ALPR). The criteria we used to compare the technologies are payment options, type of enforcement (manual/digital), time taken in the process, and costs - capital, operating, and maintenance. Below we discuss the pros and cons of technologies in each of the five categories. This analysis is based on an article comparing parking fee collection methods; relevant sections have been elaborated on here for your convenience (Barter, 2016).

*Digital Single Space Meters:* These meters are usually used for collecting on-street parking fee as one meter serves only one parking space. The traditional single space meters would only accept coins, but the digital ones have multiple payment options such as credit/debit cards, smart cards (ConnectCards), and coins. Some manufacturers also allow contactless payment through smartphone and NFC. It enables easy price adjustments and provides access to real-time data. However, since PnRs have hundreds and thousands of parking spaces, single space meters are not feasible as it will lead to high capital and maintenance costs.

*Digital Multi Space Meters:* These are walk to meters and have features similar to single space meters i.e., multiple payment options, access to real-time data, and integration with smartphones. However, as the name suggests, multi space meters serve multiple parking spaces (the limit usually depends on the manufacturer), and hence, reduces capital and maintenance cost significantly as compared to single space meters. They also enable parking times to be extended using a smartphone. Multi space meters come in three different modes:

- **Pay-and-display:** In this mode, the users are expected to put their parking tickets in their car dashboard so that it can be verified by the lot supervisor later in the day. Although this sounds like a normal practice for car users, it is usually not suitable for motorbike users as the ticket can get lost or become wet in windy or rainy weather. Moreover, as a supervisor needs to be there physically to check those tickets, the enforcement costs can be quite high.
- **Pay-by-space:** Contrary to the pay-and-display system, users of PnRs are not required to return to their cars with their parking ticket. They can just select the space number (where they parked their car), pay the fee, and leave. While this saves some time for the users, it can create problems when people enter incorrect space numbers in the meter. This mode has a higher cost of maintenance compared to some other modes as the spaces must be marked and those markings need to be maintained.
- **Pay-by-plate:** Like pay-by-space, the users are not required to return to their cars with their parking ticket, but instead of a parking space number they need to enter their car license plate number. However, they may still need to come back (for the

first few times) if they do not remember their license plate numbers. There also might be privacy concerns for some users if it is not clear to them how/if the license plate data is used for any other purposes. Although enforcement becomes easier as the license plate numbers of parked cars can easily be matched with the numbers for which parking fee has been paid, the capital and maintenance costs are similar to the pay-and-display system.

*Pay-by-Phone:* Pay-by-Phone is a technology that enables contactless payment of parking fee. Similar to the different modes under Digital Multi Space Meters, a user can enter either a parking space number, small parking zone number, or the license plate number. While these are often used as a complement to the space meters, they can also be used as a standalone fee collection technology. Pay-by-Phone has different variations but all of them can be implemented with very small investment. They all support multiple payment methods, except coins and NFC. Three variations we researched include:

- Pay-by-Smartphone App: Examples of this technology can be seen in different Pittsburgh benchmark cities, such as Portland (Parking Kitty App) and Boston (ParkBoston). It is usually very fast if the app is downloaded, and the account details and license plate are pre-registered. Every transaction might charge a little extra than the parking fee as a transaction fee, but that is negligible. As only those riders who own a smartphone can use this technology, for others with no smartphone, an alternative fee collection technology must be in-place (probably one of the multi space meters).
- Pay-by-Phone Call: With this method the PnR users can pay for the parking fee by calling on an automated phone line and entering details. Although this technology does not require much investment and is suitable for users without a smartphone, the process can be unnecessarily time-consuming, which can frustrate regular users.
- Pay-by-SMS: Users can also pay for parking by sending a text message in a desired format to a number. They are charged for the parking fee from their cellular service provider later. A drawback to this method is that it is also limited to people who have a charged cell phone with service at the lot, and the message might not be accepted if the format is inappropriate.

Radio Frequency Identification (RFID) with barriers: This is one of the automated parking management systems that is widely used these days in gated communities and business/university parking garages. It is a hands-free drive through parking system and requires almost no time to be spent by the user in the process. The entire process contains three components - first registering for the RFID tag and paying a fee (monthly or annual) in advance (a web portal can make this readily accessible), allocating unique RFID hang/windshield tags, and installing RFID readers with barriers in the PnRs' entrance. Although this is an advanced technology, it is relatively economical and as the entire process is automated there is no enforcement cost. However, this technology is better suited for reserved parking setup because new/infrequent users won't have RFID tags and hence, they won't be able to use the parking lot.

Automatic License Plate Recognition (ALPR): The ALPR parking system involves installing cameras at PnRs and using sophisticated software. Despite it being first introduced in the 1970s, it is still one of the most advanced and most costly technologies for parking fee management. Like the RFID, it is a hands-free drive through system and will require pre-registration of license plates before usage. This technology also makes sense in a reserved parking setting and might require additional investment for infrequent PnR users (such as any one of the multi space meters). Because the entire process is automated, adjusting prices is easy (if required) and no lot supervision is required for enforcement.

Table 3 in the Appendix shows a summarized comparison of each of these technologies. Overall, there are many different parking fee collection technologies and capital, maintenance, and enforcement costs vary significantly between them. As technology is getting better and cheaper every year, we would recommend that PAAC keep an eye on emerging technologies and how best they might be used when considering the needs of PAAC commuters.

### **3.4 Transit Preference Modeling**

One of the major hesitations surrounding the implementation of a charged parking system is the uncertainty related to its reception and the resulting changes in utilization. It is always possible that charging for parking will lead to a loss of revenue as PnR users could easily transition to driving and the implementation itself is not without cost. Based on our research and the interests of our contacts at PAAC, we chose to develop a Mode Choice Model (also known as a multinomial logistic regression model) to help understand how commuters make decisions about which mode of transit to use. These models are commonly used in transportation research because they are readily statistically interpretable and conveniently model the well-regarded notion of decision making by maximizing utility (Li B. , 2021).

Essentially, mode choice models work by estimating utility functions to model how commuters value different modes of transportation. These utility functions consider features of the individual commuter such as age, income, or gender as well as features of the individual possible modes of transit such as the total cost, total commute time, and the overall reliability. Once these utility functions have been modeled, making a prediction about the impact of a pricing change or service frequency change is a straightforward process. Other researchers have used this type of model to look at the impacts of various changes on PnR demand in other countries, which makes it a promising model to consider for our purposes (Li, et al., 2017) (Zhao, Li, & Xia, 2017).

## **4. Analytical Approach**

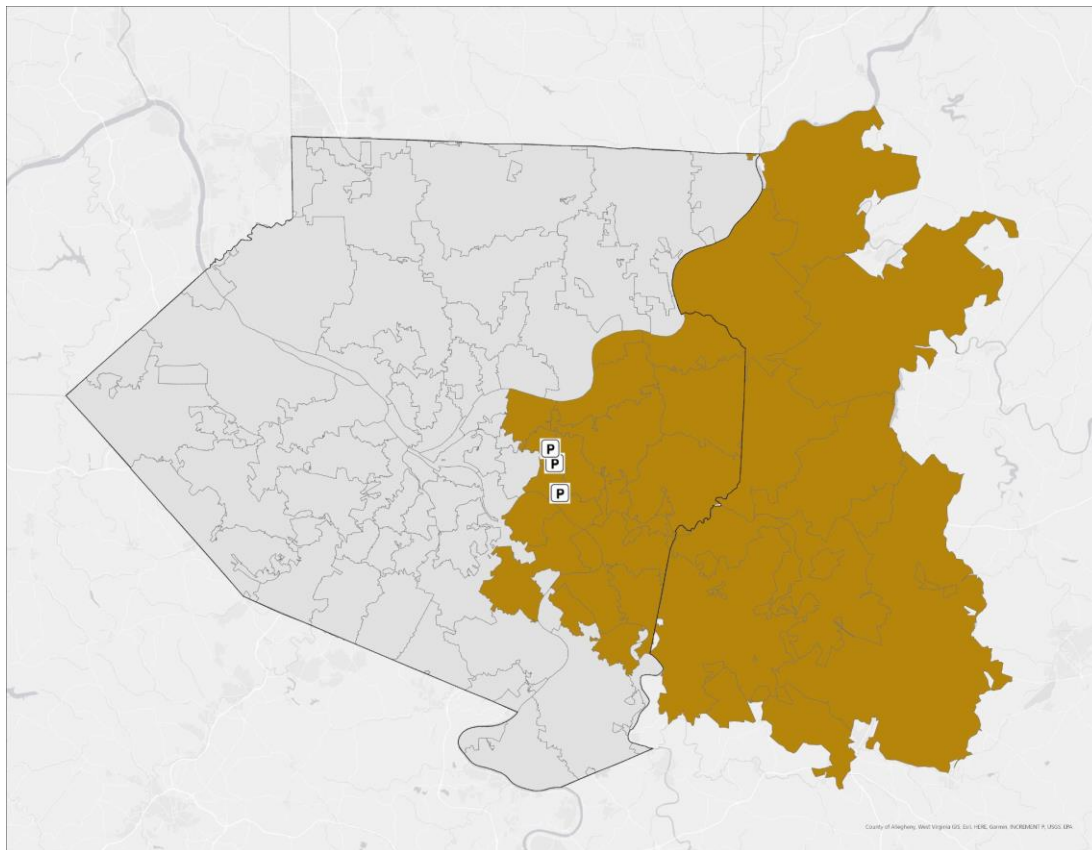
### **4.1 Model Overview**

We selected a mode choice model because it can be used to predict the change in utilization of PnRs if a parking fee is implemented. Given our time constraints, we decided to construct a model focused on the East Busway, which includes the PnR lots of Wilkinsburg, Hamnett, and Swissvale. Narrowing the scope of the model allows for a simpler model; calibrating a model for the entire PnR system would require more features



to be collected and more assumptions that could limit its usefulness in decision-making. We selected the East Busway because all of the PnR lots are owned by PAAC and many people use it to commute to Downtown and Oakland. Additionally, all three East Busway PnR lots have high utilization rates (greater than 90%), which make them good candidates for implementing a parking fee.

Because we focused the model only on the East Busway, we limited our analysis to zip codes where commuters may use the East Busway and attempted to excluded areas where commuters may be likely to use other modes of transit not included in our model, such as PnRs in other parts of the county or the light rail system. We also used the PnR 2017 license plate analysis shared by the Southwestern Pennsylvania Commission (SPC), which identified the zip code of cars parked at various PnR locations, to help identify the zip codes of possible Wilkinsburg, Hamnett, and Swissvale PnR users. Figure 4 shows the map of zip codes included in our model with the three East Busway PnRs marked at their location.



*Figure 4: Map showing the regions from which commuters travel in our dataset in yellow. The three East Busway PnRs are marked with “P” on the map, and the grey outlined area shows the boundaries of Allegheny County.*

Our model assumes that commuters have three travel mode options to choose from to reach their destination of Downtown or Oakland - Driving, Bus, or PnR. Because the number of observations at each of the three PnR lots are relatively small, we collapse them into one PnR mode rather than considering them as separate modes.<sup>5</sup> These three modes of transit represent over 95% of commuter travel from the areas we selected to Downtown or Oakland, hence the exclusion of walking or biking as modes. The table below shows how users are classified into the three modes based on their preferred travel route.

Mode Option	Travel Route
Driving	Origin → Destination
Bus	Origin → Walk to bus stop → Take bus(es) to destination
PnR	Origin → Drive to PnR → Take East Busway to destination

*Table 2: Description of the three different commute modes considered.*

Commuters that walk up to the East Busway are classified as choosing “Bus” as their mode of transit. Only commuters that drive to either the Wilkinsburg, Hamnett, or Swissvale stop are counted as PnR users.

$$mode \sim reliability + total\_cost + total\_cost:total\_time | income\_under50k + total\_distance$$

*Equation 1: Formula used to create the Discrete Mode Choice Model used for this analysis.*

The model we trained is a multinomial logit model (a type of Discrete Choice Model, formula shown above), which predicts user behavior by approximating the utility of each mode to an individual commuter. The first three features that we used, reliability, total cost, and total time, are mode-specific. That is, total cost represents the total cost to an individual commuter that would result in choosing each possible mode. In a multinomial logit model, attributes of all the alternative modes are required, not just the alternative that the commuter chooses; this allows the model to evaluate how good that commuter’s other options were. Total time and total cost are highly negatively correlated because cheaper modes of transit tend to take more time than more costly ones. Because of this,

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<sup>5</sup> We ran the model with three PnR modes, but it did not pass important validity tests due to the small number of observations at Swissvale and Hamnett, hence the decision to collapse the modes into one PnR mode.

we could not include those two variables separately, but we decided to include the interaction of total time and total cost in case the length of an individual's commute impacts the amount they would be willing to spend to shorten it. For individual commuters, we also considered income data and the total distance of their trip as we thought those factors might also influence a person's decision regarding how to get to and from work each day.

## **4.2 Data Sources**

It was important to us that the model we built be readily modifiable and updatable. All the data sources we used are updated on a regular basis, so if the problem and model is re-examined in the future, the resources to do so should be readily available.

*Make My Trip Count (MMTC) 2018:* The Make My Trip Count dataset is a survey of commuters in the Allegheny County region conducted in 2018. The survey measures what modes of transportation respondents use to commute to work and the obstacles they face on their way, along with their demographics, such as gender, annual household income, etc. We use a subset of the dataset consisting of respondents who live East of Pittsburgh and who commute to Downtown or Oakland (shown earlier in Figure 4). As this survey is conducted by collecting voluntary responses from Allegheny County residents, a limitation of this dataset is that it is not a random sample of commuters and therefore may not accurately represent all commuters in our study area. However, to generalize our model results we assumed that the MMTC survey dataset is a representative sample of the commuter population living in the eastern part of Allegheny County.

*Google API:* From the subset of MMTC dataset, we gathered the destination (i.e. Downtown or Oakland) and geo coordinates of origins.<sup>6</sup> For simplicity, we assumed that those who are commuting to Downtown are ending their commute at Smithfield and Sixth, and those commuting to Oakland are ending their commute at the Cathedral of

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<sup>6</sup> Origin geo coordinates are the center of the Census block that the MMTC commuter identifies as their origin

Learning.<sup>7</sup> As described earlier, commutes by PnR involved two parts, and hence, had two sets of origin and destination pairs - (Origin → PnR), and (PnR → Destination). To get travel distance and time for the Driving mode, we used Google Maps' Distance Matrix API. However, for the Bus mode, we needed additional information regarding the bus route (to compute reliability and waiting time at the bus stop), which is why we used Google Maps' Directions API.<sup>8</sup>

PAAC Reliability and Schedule Data: We used Port Authority's monthly on-time performance data for the relevant transit routes in our model to construct a reliability feature.<sup>9</sup> Because the model cannot account for seasonality in on-time performance, we used an annual pre-pandemic average for each transit line.<sup>10</sup> We also used the headway information during the weekday morning peak from the Port Authority's schedule data to determine wait times for each bus.<sup>11</sup>

### **4.3 Data Analysis**

Once the data for our model had been collected, we performed some exploratory data analysis to understand how mode choice is connected to different variables of interest.

Number of Commuters Per Mode: The initial data exploration task involved identifying commuters using each one of the mode choices. The MMTC dataset included questions about the preferred mode for each commuter. Commuters who chose driving to a PnR and parking there were asked about the PnR location at which they preferred parking. These two questions were essential in building the model. Because the project only considered commuters using or who could have used the East Busway to get to their

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<sup>7</sup> Geo coordinate used for Smithfield and Sixth and Cathedral of Learning are (40.4414, -79.9977) and (40.4451, -79.9533) respectively

<sup>8</sup> Although these APIs are paid, we used the free credits provided by Google Cloud. Using either of the two APIs also requires a private key, which has not been shared with the code but can be created free of charge.

<sup>9</sup> Data accessed from the Western PA Regional Data Center (WPRDC).

<sup>10</sup> Average monthly on-time percentage from February 2019 to February 2020.

<sup>11</sup> Pre-pandemic schedule data from November 2019 to March 2020.

destinations in Downtown or Oakland, the number of commuters included was 2093. Table 3 shows a breakdown of commuters in each mode choice.

Mode	Number of Commuters in Dataset	Median Total Distance (miles)	Median Total Time (mins)	Median Total Cost (\$)	Median Reliability (%)
Drive	1223	14	21	25	100 <sup>12</sup>
Bus	796	9	42	5	61
PnR	74	11	41	11	80

Table 3: Median values for model variables broken down by preferred mode of transit.

The fact that the most popular mode was driving indicates that there are many commuters who own cars and currently drive to their destinations. This means that if charging for PnRs causes current PnR users to switch modes, there is a large market of potential PnR users who may have been driving due to overcrowded parking lots.

*Exploring Model Variables:* Total distance, total time and total cost were analyzed for each mode and compared to gain a better understanding of the distributions of the variables of the model. The results of this analysis are also summarized in Table 3 above.

Looking at the median total distance for each mode shows that commuters who choose to drive tend to travel farther than commuters who use buses or PnRs as their primary modes of transit. Even though commuters who drive travel farther on average, their commute times are much shorter than those of bus riders and PnR users. This data agrees with the intuitive understanding of why commuters may prefer to drive even though it is more costly than using public transportation.

These three variables combined paint a picture of how commuters make decisions.

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<sup>12</sup> Driving was assumed to be perfectly reliable because on time percentages could not be reliably estimated for the myriad of routes considered.

- Commuters who choose to drive can travel greater distances in shorter periods of time but incur a much higher cost of total commute.
- Commuters who take the bus tend to travel shorter distances and pay much less than commuters who utilize other modes but have significantly longer commute times.
- Using an East Busway PnR gives cost, time, and reliability values somewhere in between the two alternative modes.

### Commuter PnR Choices

Within the PnR category, three PnRs were considered: Hamnett, Swissvale and Wilkinsburg. Table 4 shows the number of observations in our dataset for each PnR.

<b>PnR</b>	<b>Number of Observations</b>
Hamnett	12
Swissvale	10
Wilkinsburg	52
<b>Total</b>	<b>74</b>

*Table 4: The number of commuters in our data set who preferred each of the different East Busway PnRs*

One question we wanted to explore was how commuters chose which PnR to use. What we observed was that PnR users generally drive to the PnR which minimizes their total commute time and not the PnR that results in the shortest driving distance.

This pattern was particularly noticeable among commuters who used the Wilkinsburg PnR. Over 70% of Wilkinsburg PnR users in our dataset parked there even though one of the other two PnRs is closer to their home.

Interestingly, for commuters using the Swissvale PnR, Swissvale tended to be both the closest PnR and the PnR that resulted in the shortest total commute time.

## 4.4 Model Features

Data collection necessarily involves assumptions that need to be made to get structured interpretable data that is useful for further research. This section explores features used in our model along with some assumptions that were used to edit data used in model building.

*Total Travel Time:* Total travel time was calculated as the time in minutes required for the morning commute<sup>13</sup> which is the sum of the driving time, time spent waiting for a bus, time spent walking to a bus, and the time spent traveling on the bus. Each of these features was estimated using the following methods.

- Driving Time - Driving times were calculated using the Google Maps Distance Matrix API.
- Walking Time - Walking time was calculated for the mode “Bus” using the Google Maps Directions API. Walking time for modes where people drive either to their destination or to a PnR were assumed to be zero.
- Waiting Time - Waiting time was calculated using PAAC data on bus frequency during morning rush hour. For buses which run frequently (one bus every ten minutes or less), waiting time was approximated as half of the headway.<sup>14</sup> For buses which run less frequently, waiting time was assumed to be 5 minutes.
- Transit Time - Bus transit time was calculated using the Google Maps Directions API.<sup>15</sup>

Driving and bus transit time calculations are optimistic for two reasons. First, travel time data from the Google API is pandemic-era, so traffic congestion is lower than normal. Second, the Google API returns the optimistic time estimate (i.e., if Google maps estimated travel time as 18-25 minutes, the API would return 18 minutes). As a result, the model may overinflate the importance of commute time and thus favor driving.

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<sup>13</sup> We assume commuters either arrive at 9 A.M. or depart at 8:15 A.M.

<sup>14</sup> For people using the Wilksburg PnR to commute to downtown, two buses (P1 and P2) are possible so waiting time was calculated from their combined headway.

<sup>15</sup> We requested the bus route that minimizes the number of transfers from the Google API.

Total Cost: Total cost was calculated as the round-trip cost for a given mode of transit which includes the total round trip driving cost, the total round trip bus fare, and the average parking cost at the destination. For PnR users, the round-trip cost was calculated as the cost of driving to and from the PnR lot plus round-trip bus fare. Each of these features was estimated using the following methods.

- Round trip Driving Cost - Driving distances were calculated using the Google Maps Distance Matrix API, and driving costs were estimated as \$0.575 per mile driven based on the 2020 IRS standard mileage rates (IRS, 2021).
- Roundtrip Bus Fare - Bus fare was estimated as \$2.50 for each bus taken because regular bus commuters would be likely to have a ConnectCard and pay the associated reduced fare. This does not account for commuters who may have a personal monthly bus pass or one through their employer. For that reason, this assumption may inflate the cost of using the bus and thus cause the model to favor driving more heavily.
- Average Parking Cost at the Destination - Hourly, daily, and monthly parking fees were collected from lots in Downtown and Oakland.<sup>16</sup> The cheapest parking mode was typically to have a monthly lease, so parking fees were estimated as the average daily rate given a monthly lease and assuming 22 workdays per month.<sup>17</sup>

Reliability: Reliability was measured as the on-time percentage for a given mode of transit. For driving, reliability was assumed to be perfectly reliable with a score of 100%, and for modes using a single bus the reliability was given as the average on time percentage for that bus route. For modes including a bus transfer, reliability was taken to be the product of the on-time percentages for each bus taken.

Income: Income in the MMTC dataset is a categorical variable, meaning that respondents selected one of many annual income brackets. We chose \$50k as the threshold income because we felt that individuals earning above that amount were likely to be less price sensitive than individuals earning less than that. Given that assumption, we collapsed the

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<sup>16</sup> See appendix Table 4 for summary of data collected

<sup>17</sup> \$13.18 per day for Downtown, \$6.78 per day for Oakland



income data to create a binary variable called “income\_under\_50k”. We assumed that the respondents who preferred not to mention their income or left it blank earn less than 50k. Importantly, this is individual, not household, income data, so total household earnings of commuters may differ significantly from what is recorded.

#### **4.5 Assumptions and Limitations**

The above section describes the key model features and the assumptions that were made to build the final features. There are also several modeling assumptions made when constructing the model that are important for understanding the model limitations. These assumptions are described below.

*No latent demand:* As the literature review suggests, PnR utilization tends not to decrease much when parking fees are implemented or increased when the utilization of the lot is high (i.e., greater than 90%) (National Academies of Sciences, Engineering, and Medicine, 2016). This is often because of the existence of latent demand - there are more drivers that would like to use the lot than the lot can physically accommodate. If latent demand exists, then even if some users decide to no longer use the lot because of the price increase, new drivers will fill the newly available spaces. Our model assumes there is no latent demand because there is no data on whether this demand exists and if so, to what extent. Therefore, our model predicts the change in parking utilization for existing users. The overall change in parking utilization will be lower than predicted if there is latent demand.

*All modes available to every individual:* The MMTC survey does not ask respondents whether they have access to a car for their commute, so for bus riders it is not possible to tell if they are choosing that mode out of preference or necessity. For our analysis, we assumed that all commuters in our dataset had access to a car. This seemed reasonable given that most of our included regions are rural, but if we had had access to accurate data regarding this feature, the model data set could have been modified to incorporate that information. Moreover, during the data exploration, we found out that some respondents do not have access to buses as they live far away from the transit lines. However, we

assumed them to have the option of taking a bus from the origin and imputed a large travel distance and time to minimize the probability of taking that mode.

*All data points are independent:* Because one of the assumptions of the multinomial logit algorithm is that the dataset should satisfy the i.i.d condition (i.e. independent and identically distributed), we also assumed that the data points in the MMTC dataset are independent and are from the same distribution. This means that we believe that each commuter has filled only one MMTC survey form and any respondent's answers are not influenced by any other respondent.

*Psychological pricing effects are unaccounted for:* Our model predicts change in mode choice behavior due to an increase in the round-trip cost, and thus may not accurately capture how people respond when parking changes from being free to being charged. PnR users will likely be resistant to paying for a benefit they are accustomed to getting for free. Additionally, in our model we assume a per mile cost for driving but many drivers regard driving as “free,” so actual drivers may overinflate how much a modest parking fee contributes to their daily commute cost.

## 5. Model Results

A Multinomial Logit Regression was used to model the choice between the three alternatives — Driving, Bus, and PnR — for commuters on the East Busway traveling to Downtown or Oakland. This model was implemented using the 'mlogit' package in R and calibrated with the dataset described in Section 4 of the report. Using this statistical method, we modeled log-odds of choosing Bus or PnR compared to Driving as a linear combination of alternative-dependent and alternative-independent features. A summary of the model output can be seen in Appendix Figure 1. Below is the mathematical representation of the model results. Coefficients of the variables in these equations can be interpreted similarly to the coefficients in a Logistic regression ([interpreting odds ratios in Logistic regression](#)).

Log-odds of choosing Bus w.r.t. Driving =  $-0.083 + 0.006 * \text{Reliability} - 0.127 * \text{Total Cost} + 0.00014 * \text{Total Cost} * \text{Total Time} + 0.796 * \text{Income less than 50K? (binary)} - 0.199 * \text{Total Distance}$

Log-odds of choosing PnR w.r.t. Driving =  $-2.797 + 0.006 * \text{Reliability} - 0.127 * \text{Total Cost} + 0.00014 * \text{Total Cost} * \text{Total Time} + 0.202 * \text{Income less than 50K? (binary)} - 0.102 * \text{Total Distance}$

## 5.1 Total Cost

The fitted Discrete Mode Choice Model confirms our assumption that the total cost of the trip plays a significant role in choosing between the transit modes. Additionally, the negative coefficient on the ‘Total Cost’ variable indicates that a commuter is less likely to choose a particular mode when there is an increase in the cost of using that mode. Furthermore, the positive coefficient for the interaction term ‘Total Cost \* Total Time’ indicates that cost matters less for modes with a larger commute time (i.e., commuters that use PnR or Drive are more price sensitive compared to the ones taking the Bus because they tend to have shorter commute times). This means that commuters are more likely to shift between Driving and PnR when there is a change in cost of these modes, and demand for the Bus is relatively inelastic to change in price.

Even though the model equations are useful to understand the relative importance of each attribute to the commuter while choosing between transit modes, the marginal effects of an increase in the cost of a mode on mode choice allows us to predict changes in mode utilization. Using the ‘effects’ function in the mlogit package, we were able to estimate that on an average there will be a **22.8% decrease** in demand for parking in East Busway PnRs when a **\$2 daily parking fee** is imposed.

## Total Distance

The negative coefficient of ‘Total Distance’ in the model indicates that the commuters are more likely to choose Driving over Bus or PnR for longer distances. Another way of looking at this relationship in the context of the data is that the commuters would rather drive all the way to Downtown/Oakland when the distance for which they can take the bus is a small portion of their entire commute. For example, when we consider the map highlighting the areas considered for the modeling exercise in Figure 4, a commuter driving from outside Allegheny County is more likely to drive all the way to their destination instead of stopping at a PnR to catch the Bus.

### Income

One of the mandates for Port Authority in judging merits of an initiative is to make sure that the initiative does not unfairly impact the socio-economically disadvantaged in the society. As shown in Figure 5, a larger portion of commuters using PnR have annual income more than \$50,000 compared to the commuters taking the bus. A significant and positive coefficient for ‘income\_under50k:Bus’, and lack of significance of coefficient for ‘income\_under50k:PNR’ in the model aligns with the fact that a larger portion of commuters with less than \$50,000 annual income prefer Bus over Driving or PnR. This means that if a dollar used to subsidize PnR can be diverted to improving the bus service it would benefit a larger portion of low-income commuters.

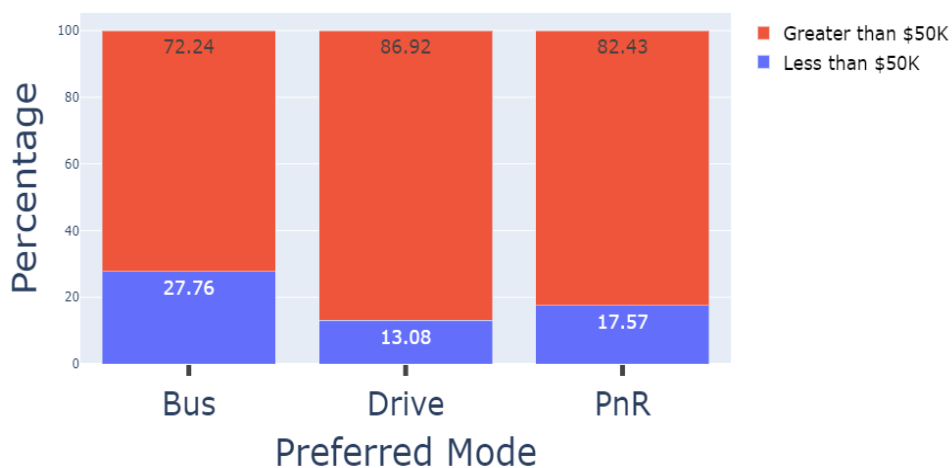


Figure 5: Distribution of income groups across the three considered commuting modes of transit

## 5.2 Implications

The Port Authority is interested in achieving three goals by collecting a parking fee at their PnRs. Their primary objective is to maximize the revenue from the parking facilities to offset the cost of maintenance, and their secondary objective is to minimize both the loss of bus ridership and the number of single-occupancy vehicle miles traveled. The loss of demand for PnR predicted by the model can be used to measure the performance of the initiative on all three project objectives.

With the assumption from our model results that East Busway PnR demand will reduce by 22.8% with the implementation of a \$2 daily parking fee, we estimate an additional annual revenue of \$64,250 and a daily loss of 170-230 PnR users to driving when a daily parking fee of \$2 is collected at the PnRs on East Busway. FIGURE X below shows the assumptions that went into this calculation.

### List of variables

Constants from Data or Literature Review		Assumptions and Values from Model	
Daily PnR Utilization in East Busway Lots	1000	Parking fee	\$2.00
Revenue per Ride	\$2.50	Loss in PnR demand	22.8%
Working Days in a Year	250	Percent of PnR Defectors Who Drive	75%
Number of East Busway PnRs	1	Average rides per park	2
Latent Demand for Parking	5%	Annual Cost of Parking Enforcement Per Lot	\$36,000.00

*Figure 6: Image showing the underlying assumptions that went into our estimated annual revenue change as a result of implementing charged parking. In our Revenue Analysis workbook, all of these values can be altered and the impacts of those alterations on the expected revenue can be readily observed.*

The underlying assumptions that went into calculating the revenue estimate can be altered using the 'Revenue Analysis' workbook included with the report. This workbook enables the decision maker to understand the outcomes for a range of values for each of

the assumptions made in calculating the metrics to measure the success on the goals of the project.

## 6. Recommendations

One of the limitations of the model we highlighted in Section 4.5 was that we did not have information on whether commuters own a vehicle or have access to one for their commute. Thus, we may be including commuters in our model who do not have the option of driving to a PnR lot as part of their commute. We suggest that in the next version of the MMTC survey, a question on car ownership or access to a car for daily commuting is included. This would allow the model sample to be restricted to the main population of interest- commuters who can choose between driving, PnR or bus- thus improving the accuracy of the model.

One of the project deliverables is the 'Revenue Analysis' workbook, which is a tool that can be used to determine how the additional revenue generated (or lost) from charging a parking fee at PnRs may vary under different assumptions. The loss in PnR demand is one of these parameters, and other variable parameters of interest may include the percent of PnR defectors who decide to drive all the way, the number of bus rides per parked car, the cost of parking enforcement, and the amount of latent demand. We recommend that the Port Authority update this tool with more precise information as it is acquired and test various scenarios with different assumptions to understand the range of possible revenue outcomes. Under our assumptions, we find that a \$2 daily parking fee would result in an additional \$64,250 in annual revenue across all the three PnR. Although this number is positive and the daily loss of 170-230 PnR users is a small proportion of East Busway daily ridership, this revenue does not fully cover the cost of maintaining the lots. Still, offsetting maintenance costs may be worthwhile, and the Port Authority will have to determine what is an acceptable revenue threshold.

Our model can provide a useful ballpark estimate of the PnR utilization change in response to a \$2 daily parking fee on the East Busway; however, there are several

variables which are not and cannot be included in the model, thus limiting its predictive accuracy. For example, we do not have data on latent demand or on the psychological effect of implementing a parking fee. To gain a better understanding of how PnR users would respond to charged parking, we suggest conducting a field trial at one of the East Busway PnRs. As Wilkinsburg is the largest East Busway lot, we suggest first implementing a daily parking fee there and closely observing how demand at that lot shifts in response.

## 7. Acknowledgements

No part of this project would have been possible without the constant guidance of Prof. Stan Caldwell. His patience and encouragement kept us on track throughout the project. We would also like to extend our gratitude to Amy Silbermann and her team at PAAC for supporting us with resources and providing us with clear direction about the goals of the project. The clarity in goal setting acted as a north star in our exploration of the problem. We also want to thank Prof. Sean Qian and Noel Lau who introduced us to the Discrete Choice Modeling techniques and went out of their way to help us with the technical formulation of the problem.

Finally, we want to thank our advisory board (listed below) for taking the time to meet with us and sharing their expertise. These meetings have shaped our understanding of the project by contextualizing the problem at hand with the experiences of people on the ground. We would not have been able to provide meaningful insights to the decision-maker without understanding the complex terrain of the policy decision.

### **Advisory Board:**

**Amy Silbermann**, Director of Planning, PAAC

**David Huffaker**, Chief Development Officer, PAAC

**Darcy Cleaver**, Manager of Passenger Amenities (including Park and Rides), PAAC

**Breen Masciotra**, Manager of Transit-Oriented Communities, PAAC

**Ellie Newman**, Manager of Transit Analysis, PAAC

**Joe Maritato**, Manager of Revenue Collection, PAAC

**Chris Sandvig**, Mobilify Southwestern Pennsylvania

**David Totten**, Southwestern Pennsylvania Commission

**Laura Weins**, Pittsburghers for Public Transit

**Gwen Bolden**, Pittsburgh Parking Authority

**Jon Caulkins**, Professor of Operations Research and Public Policy at CMU

**Sean Qian**, Professor, Civil and Environmental Engineering at CMU



## 8. Appendix

Transit Agency	Metro Area Served	Total Parking Spaces	Gross Parking Revenue (by 1000)	Percent of Parking Expenses Covered
WMATA	Washington D.C.	62,000	\$45,000	66%
BART	San Francisco	47,000	\$26,250	51%
CTA	Chicago	5,600	2,284	37%
NJ TRANSIT	All of NJ	47,000	17,500	34%
Delaware Transit Corporation	Delaware	6,300	2000	29%
MTA Metro North Railroad	New York City	25,000	5,000	18%
SEPTA	Philadelphia	24,500	4,500	17%
Santa Clara VTA	San Jose	5,300	748	13%
MARTA	Atlanta	25,350	2,552	9%
Jacksonville Transportation Authority	Jacksonville	2,957	200	6%
PAAC	Pittsburgh	6,687	306	4%
Regional Transportation District	Denver	30,000	1,000	3%
Pace	Chicago	1,024	12	1%
Triangle Transit	Durham	2,400	1	0%

*Appendix Table 1: Comparison of PnR system size, revenue amount, and percent of maintenance expenses covered from a variety of metropolitan areas across the United States (National Academies of Sciences, Engineering, and Medicine, 2016).*

Benchmark City	Daily PNR Charge	Monthly PNR Charge
Boston	\$2 - \$15*	\$35 - \$157.5*
Philadelphia	\$1	\$25
Denver	Free for the first 24 hrs. \$2 - \$4 after 24hrs	-
Cleveland	“Free” but charge extra \$0.25 for buses departing from PNR lots	-
Seattle	Variable Charge for Single Occupancy Vehicles. Free for Carpools	-
Vancouver	\$0 - \$3.75*^	-
Pittsburgh	\$0 - \$2*	\$0 - \$22

*Appendix Table 2: Daily and monthly fees for PnR usage in Pittsburgh comparison cities that charge for parking. \*indicates that the rate depends on location, and ^indicates that the amount is given in Canadian Dollars.*

Technology	Payment options	Enforcement	Time in process	Capital cost	Operating cost	Maintenance cost
Single space meters	Multiple (excl. Connect cards)	Manual	Low	High	High	High
Pay-and-display multi-space meters	Multiple (incl. Connect cards)	Manual	Moderate	Moderate	Moderate	Moderate
Pay-by-space multi-space meters	Multiple (incl. Connect cards)	Manual	Moderate	Moderate	Moderate	Moderate
Pay-by-plate multi-space meters	Multiple (incl. Connect cards)	Manual	Moderate	Moderate	Moderate	Moderate
Pay-by-smartphone app	Multiple (except cash)	Manual	Low	Low	Moderate	Low
Pay-by-phone call	Multiple (except cash)	Manual	High	Low	Moderate	Low
Pay-by-sms	Multiple (except cash)	Manual	High	Low	Moderate	Low
Radio Frequency ID	Multiple (except cash)	Digital	No time	Low	Low	Moderate
Automatic License Plate Recognition (ALPR)	Multiple (except cash)	Digital	No time	High	Low	High

*Appendix Table 3: Summary of pros and cons of currently available parking fee collection technologies (SoundTransit, 2021) (Barter, 2016).*

	Downtown	Oakland
<b>Daily Median Rate</b>	\$18.00	\$10.30
<b>Daily Average Rate</b>	\$16.93	\$10.00
<b>Monthly Lease Median (per day)</b>	\$13.86	\$6.42
<b>Monthly Lease Average (per day)</b>	\$13.18	\$6.78

Appendix Table 4: Table showing average parking costs for lots in Downtown Pittsburgh and Oakland. The daily rate represents parking costs for 8 hours or more during regular business hours. The monthly lease is the cost of a monthly lease (parking during regular business hours) divided by 22 workdays in a month. The average monthly lease rate was selected for our modeling dataset.

```
Call:
mlogit(formula = mode ~ reliability + total_cost + total_cost:total_time |
        income_under50k + total_distance, data = mc2, reflevel = "Drive",
        method = "nr")
```

Frequencies of alternatives:choice

```
Drive      Bus      PNR
0.584329  0.380315  0.035356
```

nr method

```
6 iterations, 0h:0m:0s
g'(-H)^-1g = 1.07E-07
gradient close to zero
```

Coefficients :

	Estimate	Std. Error	z-value	Pr(> z )
(Intercept):Bus	-8.3699e-02	1.6540e-01	-0.5060	0.61283
(Intercept):PNR	-2.7975e+00	3.2011e-01	-8.7392	< 2.2e-16 ***
reliability	6.2189e-03	2.6246e-03	2.3695	0.01781 *
total_cost	-1.2711e-01	1.1452e-02	-11.0993	< 2.2e-16 ***
total_cost:total_time	1.3915e-04	1.2556e-05	11.0825	< 2.2e-16 ***
income_under50k:Bus	7.9564e-01	1.2513e-01	6.3587	2.034e-10 ***
income_under50k:PNR	2.0219e-01	3.2122e-01	0.6294	0.52907
total_distance:Bus	-1.9997e-01	1.6132e-02	-12.3962	< 2.2e-16 ***
total_distance:PNR	-1.0218e-01	2.2795e-02	-4.4826	7.375e-06 ***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Log-Likelihood: -1493.2

McFadden R<sup>2</sup>: 0.10797

Likelihood ratio test : chisq = 361.48 (p.value = < 2.22e-16)

Appendix Figure 1: Summary of model output showing which variable coefficients as well as which variables are significant at different levels

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