Commuters' mode and parking decisions

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Abstract: We analyze how both fee and non-fee commute attributes affect commuters' mode and parking decisions. Results show commuters are sensitive to the price, travel time, egress time, and search time in selecting their primary commute mode, but are not sensitive to other travel costs including the costs of fuel and maintenance. Using these results we conduct policy simulations to analyze how changes in transit prices, travel times, and parking availability affect commuters' mode and parking decisions. We find raising parking permit prices and decreasing bus travel times to be effective in reducing the number of single occupancy vehicle commuters; the closure of central parking locations, however, is found to be ineffective in discouraging commuters from driving to campus as drivers are more likely to switch parking locations than they are commute modes.

Keywords: mode choice; commute; off-street parking policy; elasticity of parking; value of travel time

1 Introduction

Understanding the factors affecting commuters' mode and parking lot choices is important for at least three reasons. First, although commuters internalize the costs of congestion imposed on them by others, they do not internalize the costs they impose on society. The result is an over-crowding of single occupancy vehicles in central districts, near shopping centers, and on college campuses (Walters, 1961; Vickrey, 1963). Second, like congestion costs, commuters also fail to internalize the costs of emissions generated by their commute (Verhoef, 1994). The transportation sector within the U.S. accounts for the largest share (28.3%) of total greenhouse gas emissions, within which light-duty vehicles (including passenger cars and light-duty trucks) account for 59% of emissions (U.S. Environmental Protection Agency, 2020).[1] Third, central districts, shopping centers, and college campuses typically face expansion constraints, leaving them with too little supply to meet demand and necessitating efficient pricing/allocation strategies (Shoup, 2006). Addressing each of these concerns requires policy makers to be informed about how commuters make their mode and parking lot location decisions, so they can implement targeted policies to alleviate congestion, mitigate greenhouse gas emissions, and inform efficient pricing/allocation strategies.

Since the late 1900s, average vehicle speeds for trips within major cites has been on the decline (Couture et al., 2018); travel speeds through central London, for example, were slower in 2002 than they were in 1900, before the advent the automobile (Leape (2006); Newbery (1990), p. 35). This slowdown in traffic and increase in associated costs (fuel, time, emissions, etc.) generated growing support for additional traffic management policies to improve traffic flows. Economists (and policy makers) have long argued that perhaps a first best solution to this traffic management problem can be achieved if roads are priced at their marginal social cost of use (Leape, 2006). In 2003 London policy makers did just that; they instated congestion pricing, which required drivers to pay a £5/day fee for driving or parking within the central district. Congestion pricing encouraged commuters to use public transit, commute by bike, and make fewer trips to/through the central district. In total, the fee generated a 27% decrease in traffic in central London (Leape, 2006).

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[1]Light-duty trucks are typically used for personal travel and weigh less than 8,500 lbs. Light-duty trucks include SUVs, pickup trucks, and minivans.

Enforcing policies such as congestion pricing, however, comes at a considerable cost. Annual costs of the London congestion pricing program currently exceed £83 million/year, and while net revenues are approximately £147 million/year (Transport for London, 2019), such high costs are likely to be prohibitive in more sparsely populated regions. Alternative policies such as fuel taxes, licensing fees, or public transit expansion programs are less cost-prohibitive, but come with their own sets of limitations: fuel taxes and licensing fees mitigate total vehicle miles driven, but do not effectively manage where or when people drive (Parry et al., 2007), and public transit programs on their own have been shown to be generally ineffective in reducing total vehicle miles driven (an artifact of induced demand) (Beaudoin and Lin Lawell, 2018).

One alternative policy designed to alleviate traffic (and the associated external costs) is the direct management of the supply and costs of available parking spaces (Vickrey, 1963). Shoup (2005) describes that within the U.S., parking is 'free' for over 99% of all trips (p. 1); you likely do not pay for parking at work, at the grocery store, at your gym, or your local shopping center. The fact that parking is free in most places explains (at least in part) why 83 percent of all trips in the U.S. are made by personal motor vehicles, and only 2.5 percent are made by public transit (McGuckin and Fucci, 2018). Where parking fees do exist (at sporting events, on college campuses, etc.) they typically make up a substantial share of total driving costs, yielding the potential to divert mode and parking lot location decisions away from single occupancy vehicles and outside highly congested zones.

Several studies have investigated the effects of parking fees on commuters' mode and parking lot location decisions, generally finding that increased parking fees encourage drivers to move to less expensive parking locations and (to a lesser extent) to use alternative transit modes (Gillen, 1977; Westin and Gillen, 1978; Axhausen and Polak, 1991; Hensher and King, 2001; Tsamboulas, 2001; Washbrook et al., 2006; Harmatuck, 2007; Simićević et al., 2013; Proulx et al., 2014; Ng, 2014; Sultana, 2015; Li and Kamargianni, 2018, 2019; Khordagui, 2019; Yan et al., 2019) (see Inci (2015) for review). Most of these studies, however, either rely on stated preference choice experiments, which are generally regarded to be less reliable than revealed preference data (Hensher et al., 2015), or investigate the mode and parking lot location decisions independently of one another. Modeling the parking location decision independently of mode

choice is problematic, as parking attributes, fees for example, affect parking demand along two margins: increased parking fees encourage drivers to find alternative parking locations, but they also price some commuters out of driving altogether (Gillen, 1977). Only Westin and Gillen (1978) and Yan et al. (2019) have jointly modeled commuters' mode and parking lot choice using revealed preference data.

In this paper we add to the literature on the determinants of commuters' mode and parking location decisions using a revealed preference survey of students, faculty and staff at Washington State University. Within this study setting, we are able to fully capture the universe of commuters' mode choices, which is increasingly difficult to accomplish and a notable contribution of this work. Like Westin and Gillen (1978) and Yan et al. (2019) we also accommodate the dependencies between commuters' mode and parking lot location decisions, but we do so in a novel way. Rather than relying on structural assumptions or the nested logit framework, we jointly model commuters' mode and parking decisions using the random coefficients logit model. The random coefficients logit fully relaxes the Independence of Irrelevant Alternatives assumption, accommodates heterogeneous preferences, and allows for more flexible substitution patterns (Hensher et al., 2015). Results show commuters are sensitive to the price, travel time, egress time, and search time in selecting their primary commute mode, but are not sensitive to travel costs such as the costs of fuel and maintenance. Using these results we conduct novel policy simulations to analyze how hypothetical changes in transit prices, travel times, and parking availability affect commuters' mode and parking lot location decisions.

2   Data

Data utilized comes from the 2018 WSU Transportation and Parking Survey which included responses from 2,800 students, faculty and staff who attended or worked at Washington State University (WSU) during the 2018 academic year (WSU Social and Economic Sciences Research Center, 2018). Respondents were part of a stratified random sample, and were asked questions about their primary commute mode, attributes of their commute, and their attitudes towards campus/local transportation. Respondents who omitted their on-campus destination, their commute origin at home (city and/or cross streets), or their primary commute mode were

omitted from the analysis. The final estimation sample includes 906 individuals.

WSU is located in Pullman, Washington, which has a resident population of 34,019 and is located in the rural southeastern region of Washington State. In 2018 the University's Pullman campus had an enrollment of approximately 21,000 students, and 2,200 faculty and staff. This setting is ideal, as commuters have enough mode choices for us to conduct meaningful choice analysis but not so many that we would be unable to capture the universe of choice alternatives. This is important to discrete choice modeling and an important contribution, as capturing the universe of choice alternatives has become increasingly difficult with the advent of rideshare, electric scooters, complex transit interchanges, etc.

Commuters to WSU have four commute mode options when traveling to and from campus: walking, driving, biking, or taking the local bus service. Bus service is provided free to students, faculty and staff and the University maintains sidewalks for commuters biking or walking to campus. Both the bus service and general sidewalk maintenance are paid for through mandatory student fees. Individuals who drive also have to make a parking lot location decision. The University provides on-campus permitted parking classified into five permit zones: Orange, Green, Yellow, Red, and Blue (Figure 1).[2] Each permit allows drivers to park in the corresponding zone, with prices ranging from \$676.41/year for the centrally located and covered Orange lots, to \$129.53/year for the most distant and uncovered Blue lots. By interacting drivers mode choice with their parking lot choice we generate five drive modes, generating a total of eight unique commute modes: Walk, Bike, Bus, DriveGreen, DriveRed, DriveOrange, DriveBlue, DriveYellow.

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[2]Crimson and Gray permits are reserved for students residing in on-campus housing and are omitted from this analysis.

Figure 1: WSU Pullman Campus Parking Map
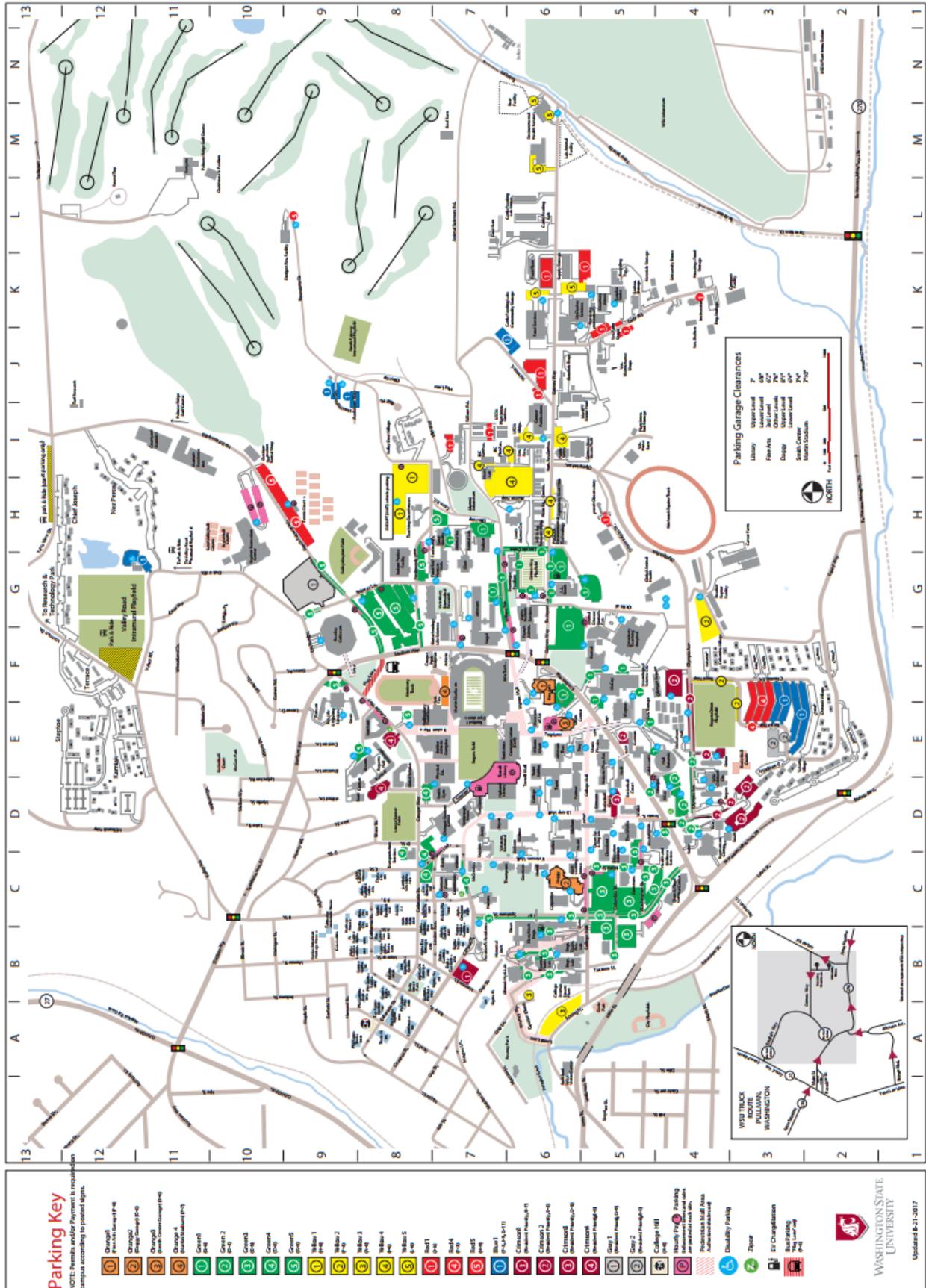
Respondents were asked to report the primary way that they usually get to campus. Almost half of respondents (42%) reported one of the driving options as their primary commute mode, with the Green zone being the most popular lot choice (Table 1). Driving is favored heavily by faculty and staff, 74% of whom report one of the driving options as their primary commute mode, while students are more likely select the local bus service or walking as their primary mode; 46% of students select taking the bus as their primary choice, 32% select walking, and only 19% select one of the 5 driving options. Biking ranks as one of the least common commute modes, with only 3% selecting it as their primary choice. (Notably, WSU sits atop a hill and commonly experiences inclement weather, both of which make biking and walking relatively strenuous.)

Table 1: Primary mode choice among all commuters

	Faculty/Staff		Students		Overall	
Walk	28	(9.2%)	191	(31.8%)	219	(24.2%)
Bike	13	(4.2%)	18	(3.0%)	31	(3.4%)
Bus	44	(14.4%)	274	(45.7%)	318	(35.1%)
DriveGreen	99	(32.4%)	44	(7.3%)	143	(15.8%)
DriveRed	22	(7.2%)	11	(1.8%)	33	(3.6%)
DriveOrange	50	(16.3%)	9	(1.5%)	59	(6.5%)
DriveBlue	10	(3.3%)	17	(2.8%)	27	(3.0%)
DriveYellow	40	(13.1%)	36	(6.0%)	76	(8.4%)
Overall	306	(100%)	600	(100%)	906	(100%)

Each transit mode is characterized by a set of mode attributes: price, travel time, travel cost, search time, and egress time (Table 2). Some of the mode attributes are self-reported as they were asked directly in the survey, while others are measured ex post. Travel and egress times, for example, are measured using the Google Maps Distance Matrix API. Given self-reported home origins and campus destinations for each commuter as inputs, Google Maps is used to calculate the travel time, egress time (walk time from parking lot to on-campus destination), and travel distance for each commuter and each commute mode.[3] Travel costs are the financial costs to

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[3]One limitation of the Google Maps Distance Matrix API is that we cannot compute historical travel times. Therefore all estimated travel times are for the summer of 2020 (when this analysis was completed), while the rest of our data is from 2018. With that said, road construction in the area has been relatively stagnant (no new route generation with significant time savings) as have been transit routes and schedules.

the individual for fuel and maintenance and are set equal to $0.30 per mile for driving modes.[4] Travel costs for bike, bus, and walk modes are assumed to be zero. Prices represent the per trip fare paid for each mode and are also equal to zero for bike, bus and walk modes. Following Yan et al. (2019) the price of drive modes is equal to the annual permit costs divided by 500 (250 workdays and two trips per day). Search times are defined as the time spent looking for a parking space and are self-reported by users of each zone. Because search times were only reported by users of each zone, the average reported search times across respondents for each permit zone was used to create zone-level attributes.

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[4]We follow Yan et al. (2019) in assuming travel costs are $0.30 per mile for driving modes, though we note that the American Automobile Association reports average travel costs to be $0.19 per mile (American Automobile Association, 2019). Results are not sensitive to this assumption.

Table 2: Trip mode summary statistics

Attribute	Alternative	Unit	Total Sample		Subsample choosing this alternative	
			Mean	Standard Deviation	Mean	Standard Deviation
Travel time	Walk	Minutes	25.25	(12.35)	15.69	(8.64)
	Bus		16.24	(7.28)	16.34	(6.16)
	Bike		9.38	(4.96)	9.06	(3.77)
	DriveGreen		6.39	(6.08)	7.84	(7.41)
	DriveRed		5.67	(6.04)	8.64	(13.75)
	DriveOrange		5.34	(5.96)	6.36	(6.25)
	DriveBlue		5.23	(5.98)	5.15	(2.16)
	DriveYellow		6.19	(6.05)	8.89	(13.66)
Egress time	Walk	Minutes	0.00	(0.00)	0.00	(0.00)
	Bus		0.00	(0.00)	0.00	(0.00)
	Bike		0.00	(0.00)	0.00	(0.00)
	DriveGreen		5.96	(4.59)	5.73	(4.59)
	DriveRed		11.87	(1.87)	11.03	(3.08)
	DriveOrange		9.58	(3.90)	8.78	(4.22)
	DriveBlue		12.75	(2.08)	12.48	(2.95)
	DriveYellow		10.00	(4.10)	9.36	(4.73)
Search time	Walk	Minutes	0.00	(0.00)	0.00	(0.00)
	Bus		0.00	(0.00)	0.00	(0.00)
	Bike		0.00	(0.00)	0.00	(0.00)
	DriveGreen		2.97	(0.00)	2.97	(0.00)
	DriveRed		1.71	(0.00)	1.71	(0.00)
	DriveOrange		1.86	(0.00)	1.86	(0.00)
	DriveBlue		3.45	(0.00)	3.45	(0.00)
	DriveYellow		1.85	(0.00)	1.85	(0.00)
Travel cost	Walk	Dollars	0.00	(0.00)	0.00	(0.00)
	Bus		0.00	(0.00)	0.00	(0.00)
	Bike		0.00	(0.00)	0.00	(0.00)
	DriveGreen		0.76	(1.61)	0.98	(2.01)
	DriveRed		0.73	(3.18)	1.34	(3.87)
	DriveOrange		0.68	(3.18)	0.72	(1.45)
	DriveBlue		0.55	(1.60)	0.46	(0.27)
	DriveYellow		0.75	(3.13)	1.33	(3.77)
Price	Walk	Dollars	0.00	(0.00)	0.00	(0.00)
	Bus		0.00	(0.00)	0.00	(0.00)
	Bike		0.00	(0.00)	0.00	(0.00)
	DriveGreen		1.00	(0.00)	1.00	(0.00)
	DiveRed		0.48	(0.00)	0.48	(0.00)
	DriveOrange		1.35	(0.00)	1.35	(0.00)
	DriveBlue		0.26	(0.00)	0.26	(0.00)
	DriveYellow		0.62	(0.00)	0.62	(0.00)

Travel times average 25 minutes and 16 minutes for walk and bus modes respectively, while travel times for drive modes range between 5 and 6 minutes. Individuals who drive, however,

also face an egress time (time spent walking from their parking spot to their final on-campus destination) which ranges from 5 minutes for centrally located lots up to 13 minutes for more distant permit zones. (Walk times to and from the bus stop are included in the bus travel time, but cannot be disaggregated from the total bus travel time.) Per trip prices for drive modes range from $0.26/trip for the distant and uncovered Blue zones up to $1.35/trip for the centrally located and covered Orange zones. The Orange zone is the only zone to offer covered parking.

Individuals who choose to walk typically live nearer to campus, as shown by the average walk time among individuals who choose to walk being markedly lower than the average walk time for all individuals (16 minutes compared to 26 minutes). Similarly, while the average drive time for each individual to campus ranges from 5-6 minutes, the average drive time among individuals who drive as their primary mode ranges from 5-9 minutes. That is, individuals who choose to drive typically live further from campus.

3   Methods

Commuters' mode choice is modeled using random utility theory. Commuters are assumed to maximize utility by choosing a commute mode from their choice set J_i of available alternatives. The set of available alternatives varies across individuals. Commute modes that are deemed unavailable or unreasonable are omitted from individuals' choice sets. The bus mode option is deemed unavailable if the Distance Matrix API returned 'NA' indicating that Google did not find a suitable bus route. Walk, bike, and bus options are deemed unreasonable if the estimated one-way travel time is in excess of 60 minutes. We have no indicator of which individuals own a private vehicle, and include driving alternatives in all individuals' choice sets. After accounting for these omissions, walk, bike, bus, and drive modes are available in 886, 897, 892, and 906 of respondents choice sets.

Then, the indirect utility of commuter i selecting alternative j is then given by:

$$U_{ij} = V_{ij} + \epsilon_{ij} = \beta_i X_{ij} + \delta_j + \epsilon_{ij} \tag{1}$$

where the indirect utility U_{ij} is decomposed into an observable component V_{ij} and an unobserv-

able error term ϵ_{ij}. The observable component V_{ij} is written as a linear function of mode and parking lot attributes X_{ij}, individual preferences β_i, and an alternative-specific constant δ_j. The error term ϵ_{ij} is assumed to follow a Gumbel (Type 1 Extreme Value) distribution.

Equation (1) represents the random coefficients (mixed) logit model. The random coefficients logit model extends the standard multinomial logit model by allowing preferences β_i to vary across individuals. In doing so, commuters' individual characteristics (such as the quality of their car, their preferences for sustainability, etc.) are allowed to affect their preferences and ultimately their commute mode/parking lot location decision (e.g. commuters' with luxury cars may be less sensitive to travel costs as they are offset by the comfort of their leather seats).

Under the random coefficients logit commuters' preferences are allowed to vary across individuals, but are assumed to follow an analyst-specified distribution, $f(\beta|\Omega)$ (sometimes called the mixing distribution). The parameters of the mixing distribution (e.g. mean and standard deviation) are denoted by the vector Ω. Conditional on β_i, the probability that individual i selects alternative j is given by the standard logit formula:

$$Pr_{ij}(\beta_i) = \frac{e^{\beta_i X_{ij}}}{\sum_{k \in J_i} e^{\beta_i X_{ik}}}. \tag{2}$$

The unconditional probability that individual i selects alternative j is then given by the integral of the standard logit formula over the density of β:

$$Pr_{ij} = \int Pr_{ij}(\beta) f(\beta|\Omega) d\beta. \tag{3}$$

4   Results

Two sets of results are presented (Table 3). The first set, in columns 1-2, are for McFadden's alternative specific constant conditional logit model (McFadden, 1974). This model is identical to that laid out in equation 1 with the omission of individual specific parameters β_i in favor of population-level parameters β. The second set of results, in columns 3-4, are for the alternative specific constant random coefficients logit model (equation 1). Under the random coefficients specification parameters Ω of the population distribution $f(\beta|\Omega)$ are estimated. Each

random coefficient is assumed to follow a normal distribution. Therefore column 3 presents the estimated population means and standard deviations of individuals' preferences (Ω in $N(\beta|\Omega)$). Post-stratification sampling weights are used to account for survey non-response and to recover parameter estimates consistent with those generated by a representative sample (Little, 1993). Notably, this weighting scheme favors students' responses, as they make up much more of the university population.

Individuals' preferences are indicated by the sign of each coefficient. The coefficients on price, travel time, egress time, and search time are each negative and significant, indicating that commuters prefer modes that are cheaper and have lower travel, egress, and search times. The coefficient on travel cost is not significant, suggesting commuters are not sensitive to the costs of fuel and maintenance. The alternative specific constants capture individuals preferences over unobserved attributes of each alternative relative to the baseline. The baseline alternative is walking. A mode with a positive alternative specific constant (all else equal) is preferred to walking, while a mode with a negative alternative specific constant is inferior. The estimated standard deviations of the random coefficients indicate the population distribution is bounded tightly around the mean coefficient, suggesting limited heterogeneity in preferences.

Table 3: Conditional and Random Coefficients Logit Models

	$U_{ij} = \beta X_{ij} + \delta_j + \epsilon_{ij}$		$U_{ij} = \beta_i X_{ij} + \delta_j + \epsilon_{ij}$	
Mode attribute parameters				
Price	-2.227***	(0.476)	-2.224***	(0.175)
Travel cost	0.003	(0.013)	0.001	(0.013)
Travel time	-0.108***	(0.011)	-0.110***	(0.012)
Egress time	-0.065***	(0.024)	-0.073**	(0.033)
Search time	-0.862***	(0.127)	-0.867***	(0.120)
Alternative specific constants				
Bus	-0.502***	(0.128)	-0.509***	(0.128)
Bike	-3.818***	(0.292)	-3.842***	(0.297)
DriveGreen	2.208***	(0.381)	2.223***	(0.242)
DriveRed	-1.347***	(0.294)	-1.353***	(0.287)
DriveYellow	-0.134**	(0.054)	-0.130	(0.188)
DriveOrange	1.086**	(0.502)	1.045	(-)[a]
DriveBlue	-0.050	(0.054)	-0.063	(-)[a]
Standard deviation of parameter distribution				
Price	-	-	0.008	(0.027)
Travel cost	-	-	0.000	(0.000)
Travel time	-	-	0.000	(0.000)
Egress time	-	-	0.044	(0.067)
Search time	-	-	0.009	(0.016)
Willingness to pay				
WTP Travel time	$2.910/hr		$2.959/hr	
WTP Egress time	$1.751/hr		$1.841/hr	
WTP Search time	$23.224/hr		$23.382/hr	
# of individuals	906		906	
# of observations	7,205		7,205	
Log-likelihood	-38,450		-38,446	
AIC	76,919		76,923	
BIC	76,988		77,026	

Notes: * p-value< .10, ** p-value< .05, *** p-value< .01. Standard errors are in parenthesis. Baseline alternative is walking. Random coefficients are assumed to be normally distributed. [a] Standard errors are missing due to non-convergence of simulated maximum likelihood covariance matrix.

The shadow value of travel time, in dollars per hour, is given by the ratio of the price and travel time coefficients, or $60 \times \frac{\hat{\beta}_i^{\text{Travel time}}}{\hat{\beta}_i^{\text{Price}}}$. Estimates suggest commuters value their travel time at $2.96 per hour, their egress time at $1.84 per hour, and their search time at $23.38 per hour. That is, commuters on average would pay $2.96 to save an hour of travel time, $1.84 to save an hour of egress time, and $23.38 to save an hour of time spent searching for a parking space. These estimates of travel and egress times are lower than those found by Yan et al. (2019), which may be driven by the high representation of students in our sample.

Choice elasticities can be calculated by taking the derivative of the estimated probability function (inputting estimates of $\hat{\beta}$ into equation 1) with respect to price (Table 4). These choice elasticities tell how a one percentage change in price will affect the predicted probability shares of each choice alternative. For example, how does a one percent increase in the price of the Green zone affect the share of commuters selecting DriveGreen as their primary mode choice? Cross-price choice elasticities can also be estimated: how does a one percent increase in the price of the Green zone affect the share of commuters who choose to walk as their primary mode choice? The row variable in Table 4 indicates the alternative changing price. Reading across the row each value is the predicted percentage change in probability share of the column variable due to a one percentage increase in price of the row variable. For example, reading across the first row shows that a one percent increase in the price of the DriveGreen will decrease the choice probability share of DriveGreen by 1.98%, increase the share of DriveRed by 0.26%, ..., and increase the share of Bike by 0.24%. Own-price choice elasticities are in bold.

Table 4: Price Choice Elasticities

	Drive Green	Drive Red	Drive Orange	Drive Blue	Drive Yellow	Walk	Bus	Bike
DriveGreen	**-1.98*****	0.26***	0.25***	0.26***	0.26***	0.23***	0.23***	0.24***
DriveRed	0.02***	**-1.03*****	0.03**	0.03*	0.03**	0.02***	0.02***	0.02***
DriveOrange	0.11***	0.12***	**-2.89*****	0.12***	0.12***	0.10***	0.10***	0.10***
DriveBlue	0.02**	0.02*	0.02**	**-0.56*****	0.02*	0.02***	0.02***	0.02***
DriveYellow	0.07***	0.08***	0.08***	0.08***	**-1.29*****	0.06***	0.06***	0.07***

Notes: * p-value< .10, ** p-value< .05, *** p-value< .01.

Own-price choice elasticities range from -2.89 in the most expensive Orange zone to -0.56 in the least expensive Blue zone. Cross-price choice elasticities range from 0.02 to 0.26. In general, the magnitudes of both own- and cross-price choice elasticities are relatively large, suggesting commuters can substitute easily between parking zones and/or non driving alternatives. The one exception is the Blue zone, which is located in far corners of campus leaving commuters with few close substitutes.
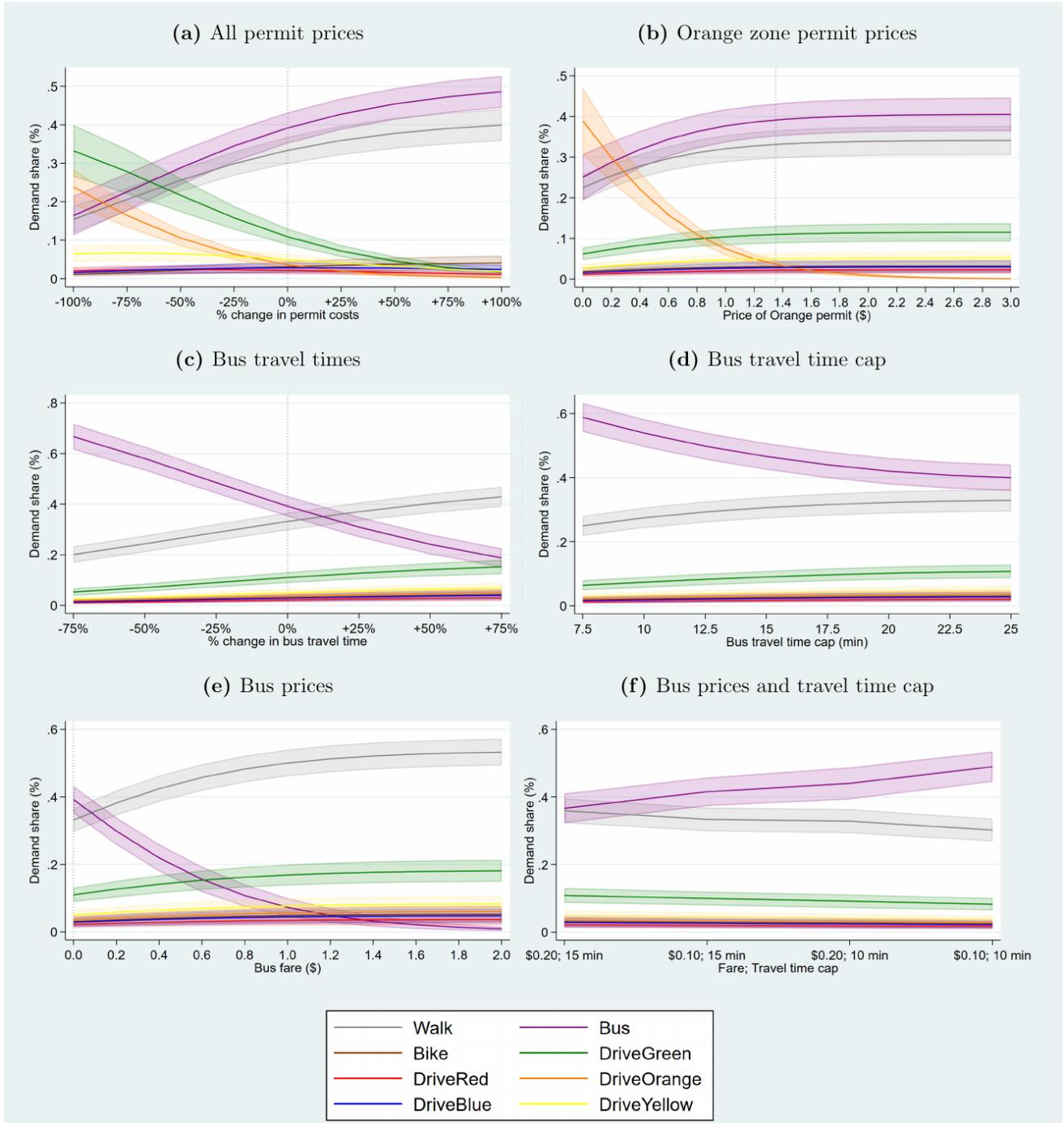
5   Policy simulations

The usefulness of these results is demonstrated through a set of policy simulations (Figure 2 and Table 5). In policy (a) the price of parking permits is varied across all zones. In policy (b) the price is varied only at the centrally located Orange permit zone. Policies (c) and (d) vary the efficiency of the public transit system: policy (c) varies bus travel times for all commuters, and policy (d) caps bus travel times leaving commuters with short bus travel times unaffected. To increase bus efficiency transit organizations may need to increase transit revenues, so policy (e) considers adding a nominal bus fare. Policy (f) combines the improved bus efficiency through caps on bus travel times (policy (d)) and increased bus fares (policy (e)). For each proposed policy demand shares are predicted for each mode (along the y-axis). In each plot the current/baseline demand shares are indicated by a vertical dashed gray line. The shaded bandwidth around each prediction represent a 95% confidence interval. One common objective of transit planners is increasing the share of commuters using non-driving alternatives; the efficacy of each policy in achieving this objective is given in the last column of Table 5.

When permit prices decrease, commuters shift their mode choices away from walking and bussing alternatives, towards driving alternatives. With permit prices cut in half, approximately 19.1% of commuters who were walking, bussing, or biking are predicted to switch to driving commute modes. When, on the other hand permit prices are increased, commuters shift from driving to non-driving alternatives. A 50% increase in permit prices from baseline, results in nearly half (45.5%) of respondents relying on the bus as their primary commute mode, with another 37.5% of respondents choosing to walk.

Dropping the price of the Orange permit zone, while holding other permit prices constant, incentives drivers to shift their parking choice to the Orange zone; this fall in prices also encourages commuters who were otherwise walking or bussing to begin driving and parking in the Orange zone. When, on the other hand, we increase the price of the Orange zone towards and beyond the choke price of $1.51/trip (effectively a zone closure), commuters shift towards walking, bussing, and other driving alternatives. Notably, this shift to non-driving alternatives is far less pronounced than the shift experienced when we increased prices at all permit zones, as drivers simply change permit zones rather than switch modes entirely.

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Figure 2: Policy simulations

(a) All permit prices

(b) Orange zone permit prices

(c) Bus travel times

(d) Bus travel time cap

(e) Bus prices

(f) Bus prices and travel time cap

Legend: Walk, Bus, Bike, DriveGreen, DriveRed, DriveOrange, DriveBlue, DriveYellow

Reducing travel times for the bus commute mode incentives commuters to take public transit, but this can be achieved in two ways. By cutting transit times across the board by a quarter, we see a 9.3% increase in bus ridership (from 39.2% to 48.5%), and when transit times are cut in half, 58.0% of commuters choose to ride the bus. Alternatively, capping bus travel times at 15 minutes is less effective in increasing bus ridership than is reducing bus travel times by a quarter (7.4% vs. 9.3%), but both policies are equally effective in increasing the share of

commuters using non-driving alternatives (+4.4%).

To cover the costs associated with reduced bus travel times, transit organizations may need to consider increasing the bus fare. Results show that increasing the bus fare from a baseline price of zero dramatically decreases bus ridership. At even nominal bus fares, commuters are quickly driven away from bussing towards either walking or driving alternatives. This is perhaps not surprising given the relatively low estimated values of travel time, and the relatively small difference in reported travel times between walk and bus modes.

The fall in bus ridership due to increased bus fares is mitigated if combined with increased bus efficiency (reduced bus travel times). At a bus travel time cap of 15 minutes and a bus fare of $0.10, we predict a 2.4% increase in bus ridership over baseline. Similarly at a bus travel time cap of 10 minutes and a bus fare of $0.20, we predict a 4.8% increase in bus ridership over baseline. If however, the travel time cap is too low and the fare too high, bus ridership will fall: at a bus travel time cap of 15 minutes and a bus fare of $0.20, we predict a 2.5% decrease in bus ridership.

Table 5: Policy simulations

	Drive Green	Drive Red	Drive Orange	Drive Blue	Drive Yellow	Walk	Bus	Bike	Δ Non-driving Alternatives
Market share									
Current	15.9%	3.7%	6.4%	2.9%	8.3%	24.9%	34.6%	3.4%	
Predicted	11.0%	2.2%	3.6%	2.9%	5.0%	33.1%	39.2%	3.1%	
Change in predicted market share									
Policy (a): increase permit prices across the board									
25%	-3.7%	-0.3%	-1.7%	0.0%	-0.9%	2.6%	3.6%	0.4%	6.6%
50%	-6.4%	-0.5%	-2.6%	-0.1%	-1.8%	4.4%	6.3%	0.6%	11.3%
Policy (b): increase price of Orange permit (current price = $1.35)									
$2.00	0.4%	0.1%	-2.7%	0.1%	0.2%	0.7%	1.0%	0.1%	1.9%
$4.00	0.6%	0.1%	-3.6%	0.2%	0.3%	1.0%	1.4%	0.1%	2.5%
Policy (c): decrease bus travel times									
-50%	-4.0%	-0.8%	-1.3%	-1.0%	-1.8%	-8.8%	18.8%	-1.1%	8.9%
-25%	-2.0%	-0.4%	-0.6%	-0.5%	-0.9%	-4.3%	9.3%	-0.6%	4.4%
Policy (d): cap bus travel time									
10 min	-3.6%	-0.7%	-1.2%	-0.9%	-1.6%	-5.7%	14.7%	-1.0%	8.1%
15 min	-2.0%	-0.4%	-0.6%	-0.5%	-0.9%	-2.5%	7.4%	-0.5%	4.4%
Policy (e): increase bus fare (current fare = $0)									
$0.10	0.9%	0.2%	0.3%	0.2%	0.4%	2.6%	-4.8%	0.3%	-1.9%
$0.20	1.7%	0.3%	0.6%	0.4%	0.8%	5.0%	-9.3%	0.5%	-3.8%
$0.30	2.4%	0.5%	0.8%	0.6%	1.1%	7.3%	-13.5%	0.7%	-5.5%
$0.40	3.1%	0.6%	1.0%	0.8%	1.4%	9.3%	-17.3%	0.9%	-7.1%
Policy (f): simultaneous change in bus fare and travel time									
$0.10; 10 min	-2.7%	-0.6%	-0.9%	-0.7%	-1.2%	-3.0%	9.8%	-0.7%	6.1%
$0.20; 10 min	-1.8%	-0.4%	-0.6%	-0.5%	-0.8%	-0.3%	4.8%	-0.4%	4.1%
$0.10; 15 min	-1.0%	-0.2%	-0.3%	-0.3%	-0.5%	0.2%	2.4%	-0.2%	2.3%
$0.20; 15 min	-0.1%	0.0%	0.0%	0.0%	-0.1%	2.8%	-2.5%	0.0%	0.3%

The final column in Table 5 summarizes the effect of each policy on the share of individuals choosing non-driving commute modes. When faced with increasing permit prices in the Orange zone (policy (b)) commuters switch to less expensive zones, resulting in little change in the use of non-driving alternatives. When on the other hand, commuters face an across the board 50% increase in parking prices (policy (a)), 11.3% of commuters who were formerly driving switch to non-driving commute modes (primarily walking and bussing). Falling bus travel times result in an increase in the share of commuters using non-driving alternatives: reducing bus travel times by 25% (policy (c)) and capping bus travel times at 15 minutes (policy (d)) both provide a 4.4% increase in the share of commuters using non-driving alternatives. Rising bus fares (policy (e)) lead to dramatic reductions in bus ridership, though many individuals switch to walking, partially mitigating the still sizable decrease in the share of individuals relying on non-driving commute modes. Combining increased bus fares with improved bus efficiency (policy (f)) results in a net positive effect on the share of commuters using non-driving alternatives: at a bus travel

time cap of 15 minutes and a bus fare of $0.10, we predict a 2.3% increase in the share of commuters using non-driving alternatives.

6   Discussion

Studies like these are useful in shaping transportation policy, and in that respect there are three major takeaways: (1) commuters are sensitive to travel times, but do not necessarily internalize other travel costs such as the costs of fuel and maintenance; (2) in response to price increases at a single parking zone, drivers are far more likely to switch lots than they are to change to non-driving commute modes; (3) reducing bus travel times is effective in encouraging non-driving alternatives, though travel time caps appears to be more cost effective than across the board efficiency improvements, as they target commuters on the margin between driving and bussing.

In addition to these qualitative takeaways, results from this work can also be used within a predictive framework to simulate proposed policies in other settings. The power of structural estimation and discrete choice modeling in particular, lies in the parameter estimates. In this setting, commuters' fundamental preferences (i.e. their utility functions) are estimated. Given these utility functions, policy makers are able to make informed predictions not only about how commuters will respond to changes in attributes of existing commute modes, but also how they might respond if we introduce new commute modes (such as parking shuttles, electric scooters, etc.). Fleshing out this prediction problem is beyond the scope of this work, but the discrete choice framework along with our estimated parameters provide a good start.

Finally, an exciting area of future research is to think about how to embed these mode choice modeling exercises within the larger transit planning efforts. To optimize transit networks, transit organizations select network characteristics including bus stop locations, frequency of service, routes, travel times, and fares. Several models have been offered to characterize and solve this multidimensional Transit Planning Problem (see Ibarra-Rojas et al. (2015) for review), however, most of these models assume ridership demand is exogenous. That is, they assume ridership demand is unaffected by the transit network characteristics. Problematically, as network characteristics (routes, frequency, fares, travel times, etc.) change so too will ridership demand;

without accounting for this endogenous change in ridership demand, solutions to network optimization problems will be wrong. One solution to this problem may be to use a mode choice model as an input to a multi objective transit planning estimator, which would allow for transit network optimization with endogenous ridership demand.

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