PARKING PLANNING TOOLS TO IMPROVE EFFICIENCIES, AID RECOVERY, AND PREPARE FOR THE POST-COVID ENVIRONMENT

FINAL PROJECT REPORT

by

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16. Abstract

This project provides parking planners at Washington State University with a tool to analyze the impacts of price changes on expected revenues and a framework for identifying optimal pricing strategies for parking. The model is flexible and can be used to estimate hourly demand. These results will help university parking planners manage peak demand by understanding the impacts of variable hourly pricing.

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SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380.
(Revised March 2003)

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EXECUTIVE SUMMARY

This project provides Washington State University parking planners with a tool to analyze the impacts of price changes on expected revenues and a framework for identifying optimal pricing strategies for parking. The model is flexible and can be used to estimate hourly demand. These results will help university parking planners manage peak demand by understanding the impacts of variable hourly pricing.

CHAPTER 1. INTRODUCTION

Washington State University Transportation Services is a self-sustaining unit responsible for managing the parking and transportation facilities and operations at Washington State University (WSU). Its employees manage over 8,300 parking spaces, including covered garages, paved lots, and unpaved gravel lots. As a self-sustaining unit, Transportation Services is required to balance its budget through the collection of short-term parking fees, annual permit sales, and parking fines. In recent years, operating costs have exceeded revenues. In fiscal year 2019 WSU Transportation Services collected $5,273,192 in revenues from parking fees, fines, and permits but incurred $5,693,147 in costs ($3,258,045 in operating and maintenance costs and another $2,435,102 in other expenses), resulting in a net loss of $419,955. Net losses were also reported in 2017 and 2018.

The aim of this project was to provide parking and transportation planners at WSU with the information they need to improve operating efficiencies so that they can better meet parking demand and community transportation needs while maintaining a balanced budget. The Covid-19 pandemic highlighted the need for crisis planning and long-term sustainability. including a plan for economic shocks.

When the WSU-Pullman campus fully re-opened in 2021 to 2022, Transportation Services faced an unprecedented challenge to recover from an extraordinary loss of many months of revenue associated with campus Covid pandemic policies. The program also needed to balance this urgency for recovery with ongoing operational and parking management decisions that would not only meet commuters' needs but do so in a financially sustainable way. Where should lots be located? How should annual permit prices be set? Which lots should be available for hourly parking? What is the optimal hourly rate? The answers to these questions are essential to increasing operational efficiencies, but parking and transportation planners typically lack access to the information they need to make informed strategic management decisions. By developing a rigorous model of parking supply and demand at WSU, this project sought to identify the critical tradeoffs that parking planners face in making operational decisions (setting rates, selecting lot locations, etc.) and to provide guidance for efficient parking management strategies.

CHAPTER 2. LITERATURE REVIEW

Although parking is an important intermediate good and is critical to land-costing, more papers have focused on when cars are moving than when they are parked (Inci, 2015). This study employed a rigorous model of parking supply and demand at WSU to provide parking and transportation planners with the information they need to make informed strategic management decisions. This method was different than the more popular mode choice models (Yan et al., 2019) in its use of administrative parking data that allowed for rigorous analysis of profit maximizing and cost recovery management strategies.

Some existing studies have tried to find price elasticities under different conditions and policies: in two meta-analyses Concas and Nayak (2012) found that the average elasticity was -0.39, while Vaca and Kuzmyak (2005) found price elasticities to be equal to -0.30. Vaca and Kuzmyak (2005) found that parking elasticities varied across users and ranged from -0.6 for those most sensitive to price changes to -0.1 for those least sensitive to price changes. Ottosson et al. (2013) conducted a case study in Seattle using a rigorous choice model and found that across time and neighborhoods, own-price elasticities ranged from -0.80 to about 0. When studying parking behaviors at SFpark (the city of San Francisco's public parking provider), Fabusuyi and Hampshire (2018) found elasticities to range from -0.45 to 0.07. Studies outside the U.S. have generated similar findings: price elasticities of parking were found to be typically negative and near zero, depending on the location and time of day. Using revealed preference data, Kelly and Clinch (2009) found that the average price elasticity was -0.29 in Durbin, Ireland, and Seya et al. (2016) found demand for residential parking in Japan to be inelastic.

This project addressed the issues of pricing multiple parking lots with separate strategies, as is common for central business districts and campus parking lots. This kind of practice respects the fact that elasticities are interdependent and vary across lots. Therefore, it is important to consider the entire system in making pricing decisions and to consider different pricing policies across lots. Filipovitch and Boamah (2016), who conducted one of only a few studies that have acknowledged this interdependence, used pricing simulations to identify optimal pricing policies at Minnesota State University. Yan et al. (2019) explored a similar idea by using survey data from the University of Michigan with a mode choice model to maximize ease of study by minimizing total search time.

CHAPTER 3. DATA AND METHODS

Parking demand data were provided by the Washington State University Transportation Services from August 1, 2019, to May 1, 2022. WSU Transportation Services scans license plates constantly in all the university-owned parking lots during the day and records the time, locations, and cars' information. We aggregated the data based on time and parking lots to calculate the hourly demand and occupancy rate for each lot.

Students and faculty can park in the parking lots by purchasing an annual permit, daily permit, paying at a parking kiosk, or paying at hourly meters. There are eight parking zones to choose from: Orange, Green, Crimson, Yellow, Red, Gray, College Hill and Blue. Before prices were increased effective July 1, 2021, the prices were $676/year, $502/year, $342/year, $308/year, $239/year, $239/year, $342/year, and $130/year, respectively. After July 1, 2021, prices increased to $776/year, $552/year, $382/year, $328/year, $254/year, $259/year, $382/year, and $145/year, respectively (Table 3-1). By purchasing the permit for one zone, drivers can park in that zone and all other less expensive zones.

Table 3-1 Parking Rates and Demand

Permit Type	Before 7/1/2021	After 7/1/2021	Price Change (%)	Occupancy Change (%)
Orange	676	776	0.15	0.62
Green	502	552	0.10	0.12
Crimson	342	382	0.12	0.15
Yellow	308	328	0.06	0.06
Red	239	254	0.06	-0.13
Gray	239	259	0.08	0.30
College Hill	342	382	0.12	-0.30
Blue	130	145	0.12	0.54

Figure 3-1 is a map that shows the locations of all parking lots at WSU, and Figure 3-2 is the map of daily average occupancy rates. In Figure 3-3, we can see how the average occupancy rates changed during a day for different days of a week, and we can see that the peak hours were from 7:00 a.m. to 4:00 p.m., which were the general times that university opened and classes ended. Figure 3-4 shows the average daily occupancy rate for different years, and it's perhaps not surprising that 2020 and 2021 experienced lower occupancy rates, on average, because of the move to online classes during Covid-19.

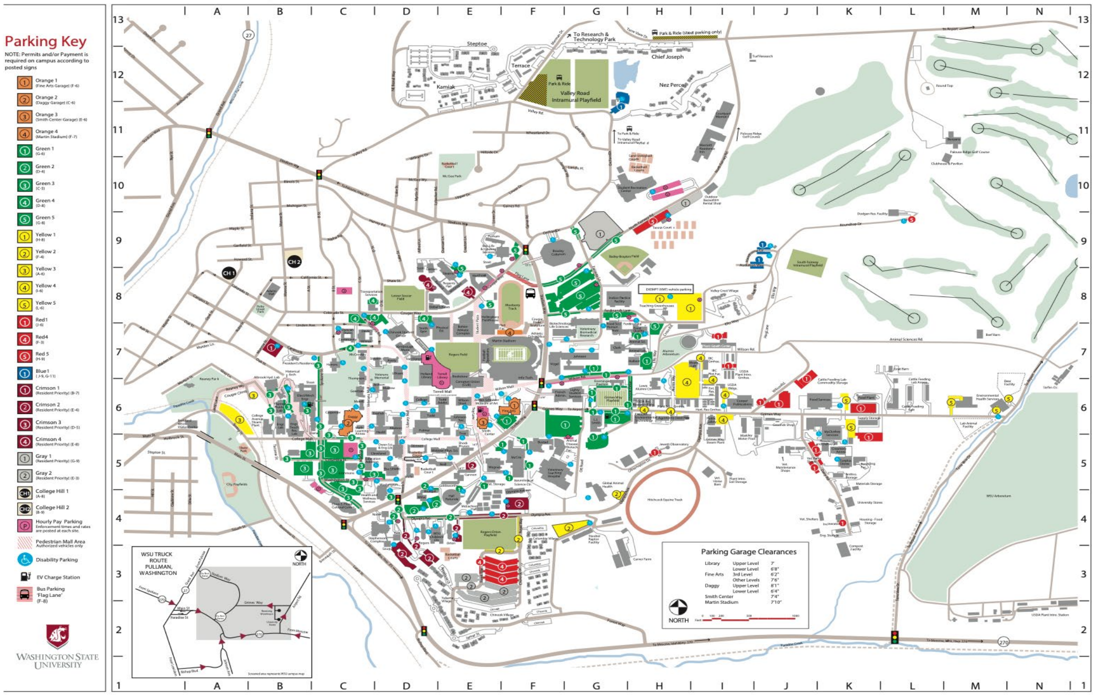

Figure 3-1 Map of WSU Parking Lots

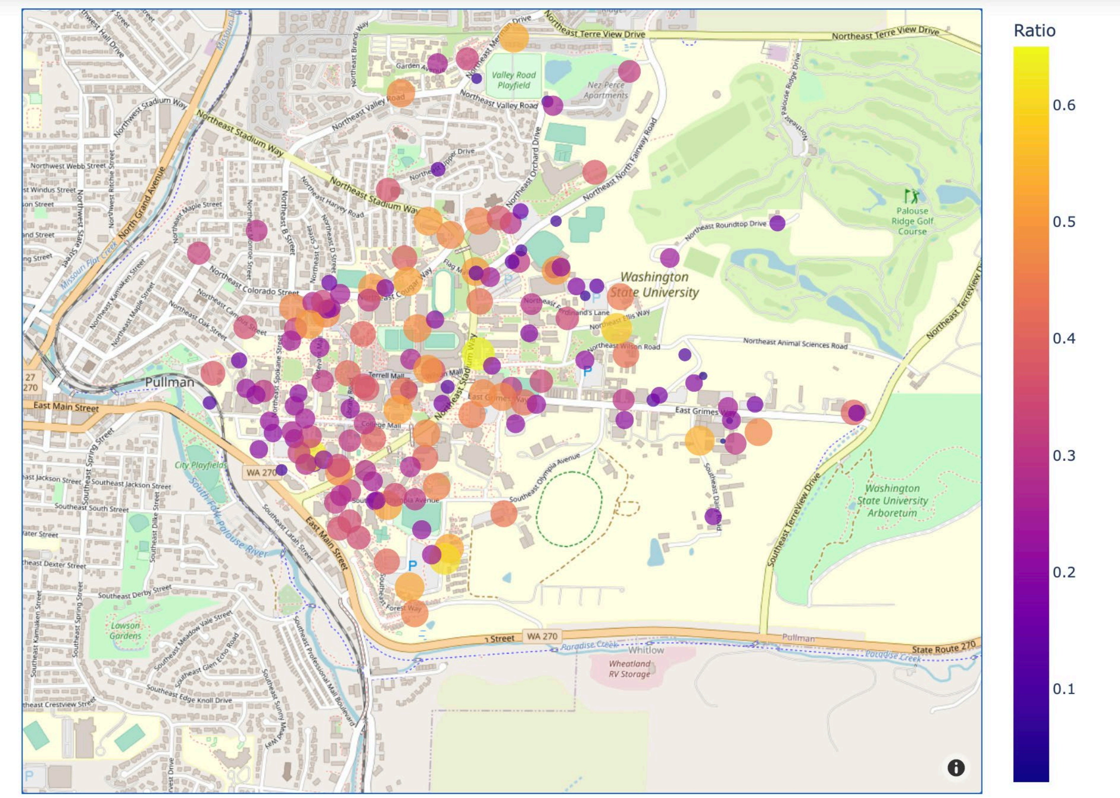

Figure 3-2 Map of Daily Average Occupancy Rates

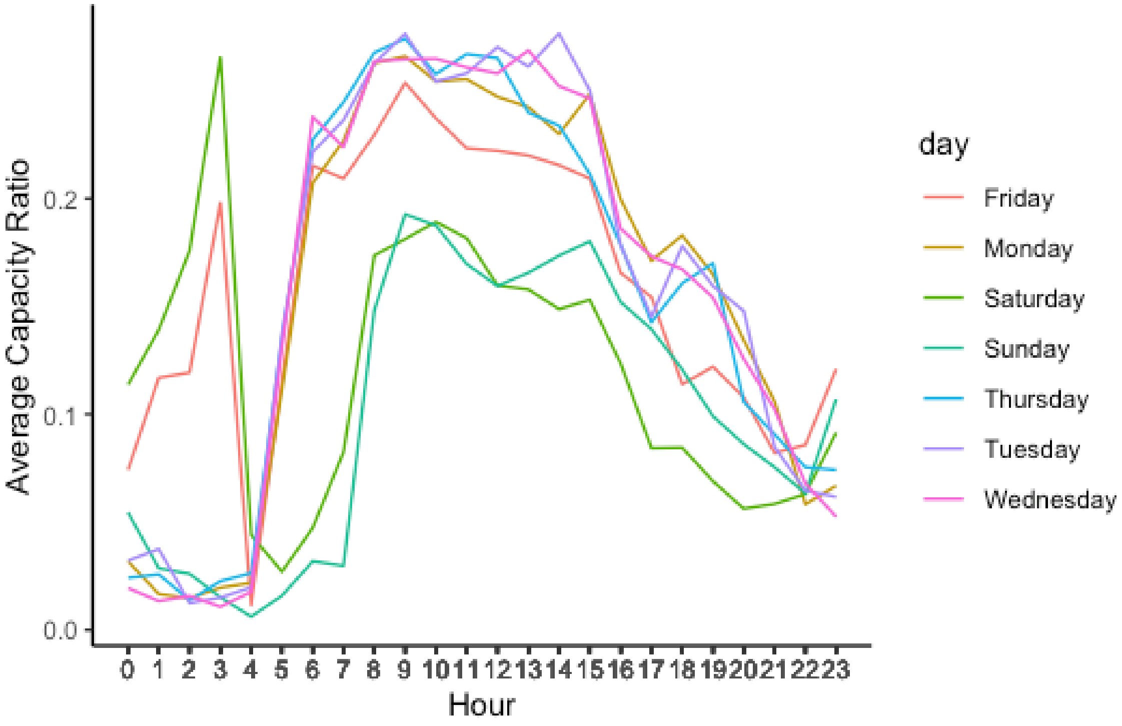

Figure 3-3 Average Occupancy Rates during a Day

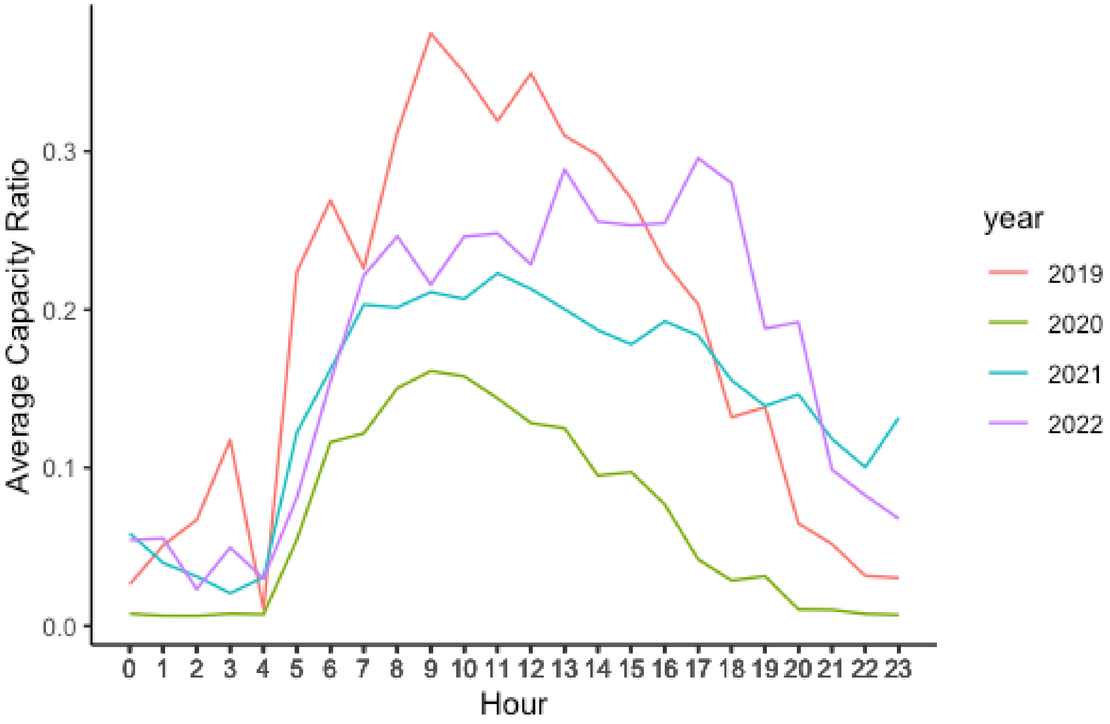

Figure 3-4 Average Occupancy Rates for Different Years

To estimate the price elasticity of parking demand at WSU, we employed models based on the work of Ottoson et al. (2013). In Model 1, we first estimated the daily price elasticities for different permits without controlling cross-price elasticities. In Model 2, we repeated the process but with hourly data, which could help us to understand how to minimize students' search time during peak hours. Then in Model 3, we built on Model 1 by adding other permit prices as controls, thereby obtaining both own-price elasticity and cross-price elasticities.

3.1. Model 1

$$\log(occupancy)_{i,t} = \beta_0 + \sigma * z_{i,t} + \beta_1 * \log(occupancy)_{i,t-1} + \beta_n * \log(price)_i * zone_n + \epsilon_{i,t}$$

where $log(occupancy)_{i,t}$ is the log term of the ith parking occupancy rate at day d (measured by the occupied space divided by total space at parking lot *i*). Every two counts of the same lot can be considered distinct only when their scan time difference is longer than 10 minutes. $z_{i,t}$ is calculated by $D_{i,t} * log(occupancy)_{i,t}$, where $D_{i,t}$ is an N*N matrix that denotes the inverse of squared distance between every two parking lots. Therefore, element $a_{i,k}$ in the matrix is the inverse of squared distance between parking lot *i* and *k*, if *i* is not equal to *k*. Otherwise, the distance of *i* and itself will be 0. $log(occupancy)_{i,t}$ is an N*T matrix in which *T* is the total number of times. $beta_1$ is the elasticity of lag occupancy. $beta_n$ is the zone *n*'s own price elasticity of occupancy, calculated separately in each hour. $log(price)_i$ is the approximate marginal price for each occurrence of parking, estimated by dividing the annual fee of parking lot *i* by 500, as we there are about 250 working days per year, and people may need to use the parking lot two times a day. $zone_n$ is the zone *n* in which parking lot *i* belongs.

After obtaining the daily price elasticities, we wanted to test whether the price elasticities were sensitive to parking lot-related features. We measured the lots' environmental variable as X_i, and the model is as follows.

3.2. Model 2:

$$\log(occupancy)_{i,t} = \beta_0 + \sigma * z_{i,t} + \beta_1 * \log(occupancy)_{i,t-1} + \beta_{i,k} * \log(price)_i * Hour_k * X_i + \epsilon_{i,t}$$

where X_i is the type of permits.

The difference between Model 1 and 2 was just that in Model 2 we included the permit type. Therefore, a different price elasticity value was generated for each type of zone at every hour.

After Model 1 and Model 2, we wanted to consider a more realistic version with other permit prices as alternatives and to calculate cross-price elasticities. However, there was a major data limitation in that the parking lots' prices changed only once over the study period, and all changed simultaneously, resulting in near perfect collinearity. Attempts to reduce this collinearity were made by using Bayesian model averaging (BMA) and partial least squares (PLS) algorithms, but to no avail. Instead, we used a compromise solution in Model 3, which used the leave-out means of all other lot prices as a control variable, from which we could derive a cross-price elasticity.

3.3. Model 3:

$$\begin{aligned} &\log(occupancy)_{i,t} \\ &= \beta_0 + \sigma * z_{i,t} + \beta_1 * \log(occupancy)_{i,t-1} + \beta_n * \log(price)_i * zone_n + \alpha_n \\ &* \frac{1}{n-1}\sum_{j\neq n}^{N} \log(price)_j + \epsilon_{i,t} \end{aligned}$$

where α_n is the coefficients for the cross-elasticity of average alternative price on the capacity of parking lots in zone n. $\frac{1}{n-1}\sum_{j\neq n}^{N} \log(price)_j$ is the average prices for other types of permits except for zone *n*.

CHAPTER 4. FINDINGS

4.1. Model Results

Table 4-1 shows our results for Model 1. The elasticity estimates for each zone represent how the occupancy rate would change (in percentage terms) when the zone price increased by 1 percent. Most of the zones had a positive elasticity except for Orange and Crimson, which means that when they were more expensive, they were more in demand. This was likely a result of unobserved zone characteristics and omitted cross-price elasticities.

Table 4-1 Model 1 Results

	Estimate	**Std error**	**p. value**
Intercept	-0.57324	0.01748	<0.0001
Lag of log capacity	0.44184	0.00346	<0.0001
Zone	**Elasticity**		
Blue	0.22890	0.01885	<0.0001
College Hill	-0.9323	0.34853	0.00748
Crimson	-0.6384	0.04511	<0.0001
Gray	0.20601	0.04019	<0.0001
Green	0.54228	0.16003	0.00070
Orange	-3.7221	0.04864	<0.0001
Red	0.17467	0.02349	<0.0001
Yellow	0.36879	0.03399	<0.0001

We also calculated hourly-specific elasticities for each zone in Model 2 (Figure 4-1 and tables 4-2 and 4-3). The general trend was that for most of the zones, the elasticity was positive during peak hours and negative for off-peak times, as people are generally less sensitive to prices in peak times. Again, these positive elasticities were likely a result of unobserved zone characteristics and omitted cross-price elasticities.

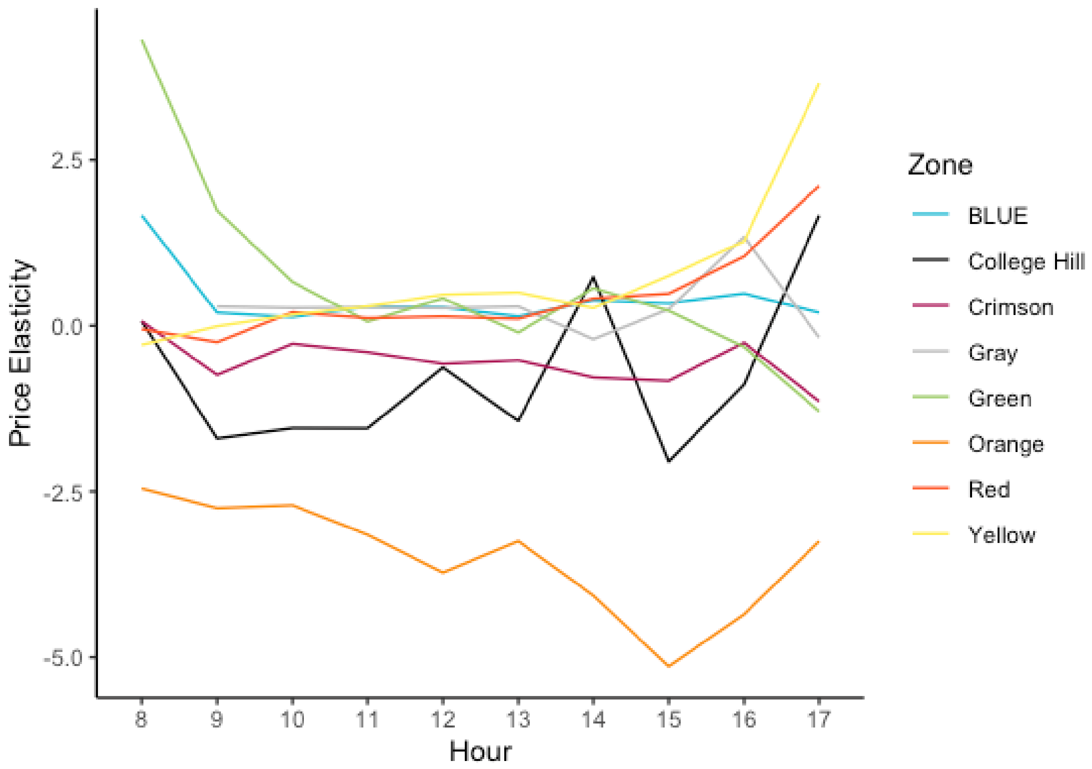

Figure 4-1 Model 2 Results

Table 4-2 Model 2 Results

	Estimate	Std error	p. value
Intercept	-0.65495	0.017791	<0.0001
Lag of log capacity	0.43189	0.00352	<0.0001

Table 4-3 Model 2 Results

Zone	Hour	Estimated	Std error	p. value	Zone	Hour	Estimate	Std. error	P value
Blue	6	0.93611	0.16456	<0.0001	Green	6	-6.33685	1.10195	<0.0001
Blue	7	-0.23435	0.11055	0.03402	Green	7	-0.07698	0.70087	0.91254
Blue	8	-0.09532	0.06199	0.12411	Green	8	3.98038	0.44861	<0.0001
Blue	9	0.21414	0.04575	<0.0001	Green	9	1.49388	0.33311	0.00001
Blue	10	0.15436	0.04552	0.00070	Green	10	0.45333	0.37200	0.22299
Blue	11	0.31056	0.04765	<0.0001	Green	11	-0.15053	0.36970	0.68389
Blue	12	0.29733	0.05065	<0.0001	Green	12	0.19337	0.39177	0.62161
Blue	13	0.16405	0.05125	0.00137	Green	13	-0.34081	0.50078	0.49615
Blue	14	0.39928	0.06373	<0.0001	Green	14	0.33929	0.49024	0.48889

Zone	Hour	Estimated	Std error	p. value	Zone	Hour	Estimate	Std. error	P value
Blue	15	0.35920	0.07163	<0.0001	Green	15	0.00205	0.47827	0.99659
Blue	16	0.51243	0.08510	<0.0001	Green	16	-0.58188	0.67205	0.38659
Blue	17	1.68744	0.27113	<0.0001	Green	17	-1.43890	1.56186	0.35691
College Hill	6	-0.38292	2.03931	0.85106	Orange	6	-5.51691	0.15289	<0.0001
College Hill	7	3.02173	2.35296	0.19907	Orange	7	-4.53861	0.13605	<0.0001
College Hill	8	-1.84837	1.28939	0.15171	Orange	8	-2.60947	0.12617	<0.0001
College Hill	9	-1.65046	1.13096	0.14448	Orange	9	-2.86985	0.11772	<0.0001
College Hill	10	-1.48103	0.60845	0.01493	Orange	10	-2.83004	0.12025	<0.0001
College Hill	11	-1.48817	1.82331	0.41439	Orange	11	-3.26328	0.11785	<0.0001
College Hill	12	-0.61270	1.13104	0.58801	Orange	12	-3.84467	0.12235	<0.0001
College Hill	13	-1.39492	1.22881	0.25631	Orange	13	-3.38411	0.12948	<0.0001
College Hill	14	0.77144	1.01945	0.44922	Orange	14	-4.19627	0.13288	<0.0001
College Hill	15	-1.94576	1.22821	0.11315	Orange	15	-5.26771	0.13563	<0.0001
College Hill	16	-0.81528	1.66515	0.62441	Orange	16	-4.50005	0.13510	<0.0001
College Hill	17	0.09992	2.03934	0.96092	Orange	17	-3.39062	0.12087	<0.0001
Crimson	6	-0.92579	0.15010	<0.0001	Red	6	2.57558	0.36708	<0.0001
Crimson	7	-1.12700	0.11801	<0.0001	Red	7	1.19754	0.17314	<0.0001
Crimson	8	-0.99854	0.11481	<0.0001	Red	8	-0.02626	0.06176	0.67067
Crimson	9	-0.70159	0.13091	<0.0001	Red	9	-0.21981	0.04984	0.00001
Crimson	10	-0.22452	0.10773	0.03716	Red	10	0.23321	0.05550	0.00003
Crimson	11	-0.35015	0.12447	0.00491	Red	11	0.14589	0.05619	0.00942
Crimson	12	-0.53195	0.12856	0.00004	Red	12	0.17080	0.06408	0.00769
Crimson	13	-0.47996	0.13807	0.00051	Red	13	0.13647	0.06196	0.02762
Crimson	14	-0.73770	0.16819	0.00001	Red	14	0.44027	0.07802	<0.0001
Crimson	15	-0.79402	0.18645	0.00002	Red	15	0.51275	0.07511	<0.0001
Crimson	16	-0.21371	0.18488	0.24771	Red	16	1.08214	0.09712	<0.0001
Crimson	17	-1.10594	0.25242	0.00001	Red	17	2.16184	0.44761	<0.0001
Gray	6	0.93080	0.15193	<0.0001	Yellow	6	2.89370	0.33135	<0.0001
Gray	7	0.28531	0.10322	0.00571	Yellow	7	0.16703	0.16121	0.30016
Gray	8	-0.61435	0.10745	<0.0001	Yellow	8	-0.23607	0.10308	0.02201
Gray	9	0.31285	0.12108	0.00978	Yellow	9	0.03868	0.07993	0.62849
Gray	10	0.31155	0.10945	0.00442	Yellow	10	0.21430	0.08021	0.00755
Gray	11	0.31360	0.11984	0.00888	Yellow	11	0.33917	0.07794	0.00001
Gray	12	0.29737	0.12282	0.01547	Yellow	12	0.51477	0.08699	<0.0001
Gray	13	0.32517	0.13613	0.01691	Yellow	13	0.55093	0.09160	<0.0001
Gray	14	-0.17217	0.14481	0.23449	Yellow	14	0.31814	0.11129	0.00426
Gray	15	0.27811	0.16299	0.08796	Yellow	15	0.79920	0.11216	<0.0001
Gray	16	1.38020	0.19604	<0.0001	Yellow	16	1.33540	0.12499	<0.0001
Gray	17	-0.13340	0.40899	0.74430	Yellow	17	3.73566	0.57429	<0.0001

Tables 4-4 and 4-5 summarize the results for Model 3. The difference between Model 1 and Model 3 is that in Model 3 we used the average alternative zone price as control variables for the cross-price effect. The coefficients in Model 3 were large in magnitude but well behaved. All own-price elasticities were negative, and all the cross-price elasticities were positive (as expected). Given a case in which all lots increased their prices by 1 percent, then Model 3 predicted that the capacity of the Blue zone would decrease by 15.04 percent because of its own price increase. However, if the average price of all alternatives increased by 1 percent, then demand in the Blue zone would increase 16.94 percent. If these two effects happened simultaneously, then the overall effect would be that the Blue zone would experience a 1.90 percent increase in its occupancy rate.

It is not a perfect model for predicting the outcomes of different pricing strategies, as the alternatives are available as average prices instead of individual permit prices for each zone. Accurately predicting zone-specific, cross-price elasticity would require more years of data and price changes. We relied on the estimates from Model 3 for the simulations described in the next section.

Table 4-4 Model 3 Results

	Estimate	Std error	p. value	Cross Elasticity	Std error	p. value
Intercept	-82.41439	26.96365	0.00224	-	-	-
Lag of log capacity	0.41393	0.00348	<0.0001	-	-	-

Table 4-5 Model 3 Results

Zone	Elasticity	Std error	p. value	Cross Elasticity	Std error	p. value
Blue	-15.04064	5.19558	0.00379	16.94964	5.53457	0.00220
College Hill	-22.08930	6.70590	0.00099	20.92343	6.95666	0.00263
Crimson	-18.02048	6.38218	0.00475	21.30848	6.95380	0.00218
Gray	-21.55468	7.77050	0.00554	18.40625	5.95148	0.00198
Green	-25.74548	8.56264	0.00264	23.67828	7.79963	0.00240
Orange	-12.60030	5.58463	0.02406	24.84002	8.47063	0.00336
Red	-29.26697	9.57798	0.00225	16.83356	5.57494	0.00253
Yellow	-31.70978	10.54206	0.00263	18.70805	6.17025	0.00243

4.2. Simulations

We conducted simulations based on both ideal cases in which we had all the cross-elasticities and the results from Model 3. The process was conducted in Excel, and it is easily repeatable for future use. For the ideal case, we obtained part of the coefficients from the

Bayesian model averaging (BMA) regression that was briefly discussed in the model section. We assumed unobserved cross-price elasticities to be equal to 0.1 and unobserved own-price elasticities to be -0.1.

We then presented two cases: 1) an increase in each of the permit prices of 20 percent and 2) an increase in every permit price of $100. The two cases could not represent all the pricing strategies that the university can use, but they provided good examples of both proportionate and disproportionate changes in prices. These simulations could be used to estimate how price changes would impact demand in each zone and, ultimately, revenues.

The results for each simulation are provided in Table 4-6. For the first case, increasing all the permit prices by 20 percent, the ideal model (with all cross-price elasticities) predicted a revenue increase of $267,152. Under the same scenario, the simulation based on the results from Model 3 predicted revenues to increase by $161,153. These increases in total revenue were driven primarily by additional revenue generated from Green zone permit purchases. For the second scenario, in which prices were increased by $100 at each zone, revenues were estimated to increase by $413,917 for the ideal model and by $537,048 for Model 3.

Table 4-6 Simulation Results

	Ideal Model	**Model 3**
Case I: Increase all permits’ prices by 20%		
Revenue Increased ($)	267,152	161,153
Case II: Increase all permits’ prices by $100		
Revenue Increased ($)	413,917	537,048

CHAPTER 5. CONCLUSIONS

This project provides Washington State University parking planners with a tool to analyze the impacts of price changes on expected revenues and a framework for identifying optimal pricing strategies for WSU parking. The model is flexible and can be used to estimate hourly demand by using the results from Model 2. These results will help university parking planners manage peak demand by understanding the impacts of variable hourly pricing. Finally, with additional data, own- and cross-price elasticity assumptions can be relaxed (and updated over time) to allow more accurate occupancy and revenue predictions.

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