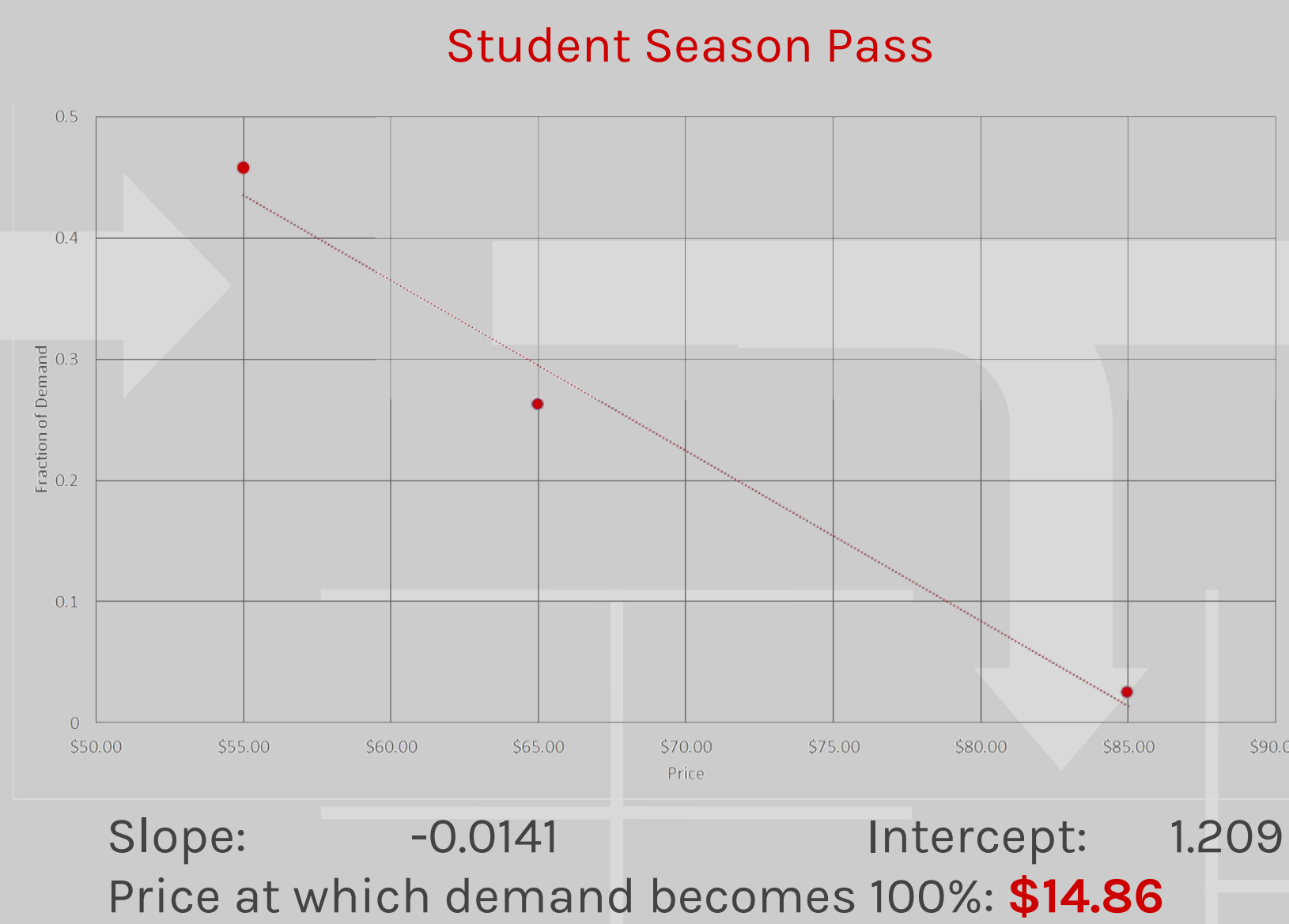
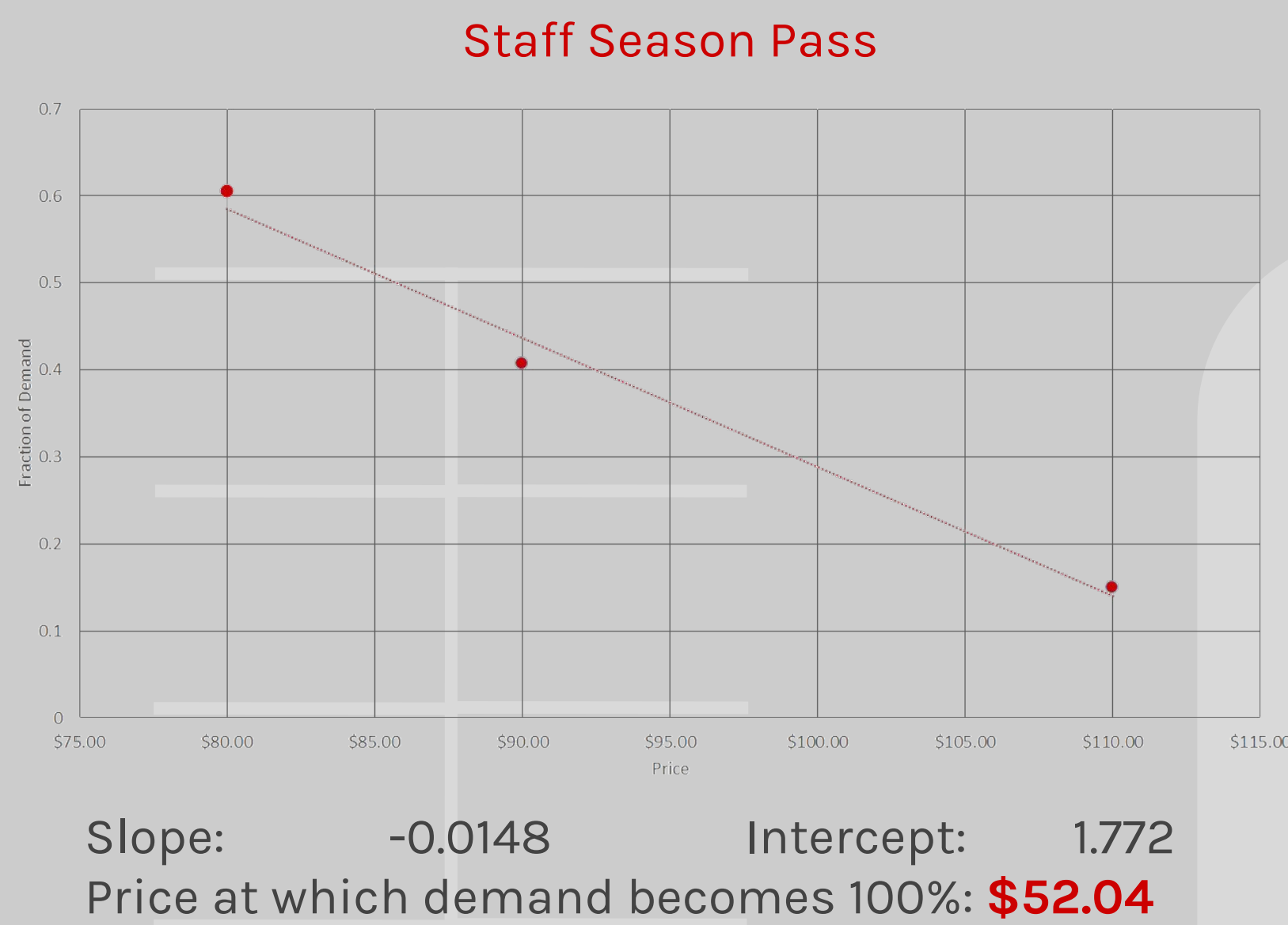


Statistical Analysis



Bonferroni Method						
Undergraduate				Faculty & Staff		
	Current vs \$85	\$55 vs Current	\$55 vs \$85	Current vs \$110	\$80 vs Current	\$80 vs \$110
Difference in mean	0.93	0.72	1.65	1.01	0.82	1.83
Critical Value (95%)	0.55	0.55	0.55	0.49	0.49	0.49
Critical Value (99%)	0.67	0.67	0.67	0.60	0.60	0.60
Analysis	<ul style="list-style-type: none">No particular price that affects demand more than othersReinforce that price always affects demand					

Regression

For each price point, the level of demand was estimated based on the responses from the survey. A regression line was calculated and extrapolated to determine the price at which demand for season parking lots would be 100%, which would be used in the revenue management segment.

ANOVA Single-Factor Experiment		
	Undergraduate	Faculty & Staff
Results	F Statistics = 27.14 $F_{0.95, 2, 126} = 3.07$ $F_{0.99, 2, 126} = 4.78$	F Statistics = 40.34 $F_{0.95, 2, 225} = 3.03$ $F_{0.99, 2, 225} = 4.70$
Analysis	<ul style="list-style-type: none">Reject Null HypothesisAt least one price point affects demand	

ANOVA and Bonferroni

ANOVA one-factor experiment was conducted, separately on the data for undergraduates and data for faculty and staff. This is to identify if there exists a particular price point that significantly affects the demand of season parking passes in SUTD. From our results, we can conclude that such an observation exists. With this result, we applied the Bonferroni method to pinpoint the exact the price point that significantly affects demand. We found that all price points significantly affects demand.

Introduction

Data Acquired

- Data collection from Campus Development
 - Survey of school members
 - Time studies of SUTD's carpark

Objective

To study SUTD's carpark with the aid of statistical analysis and revenue management so as to potentially identify suggestions to increase revenue whilst reducing season parking prices

Current Scenario

Proportion of School Population disagreeing with current pricing



Daily Carpark Occupancy



Operations Management

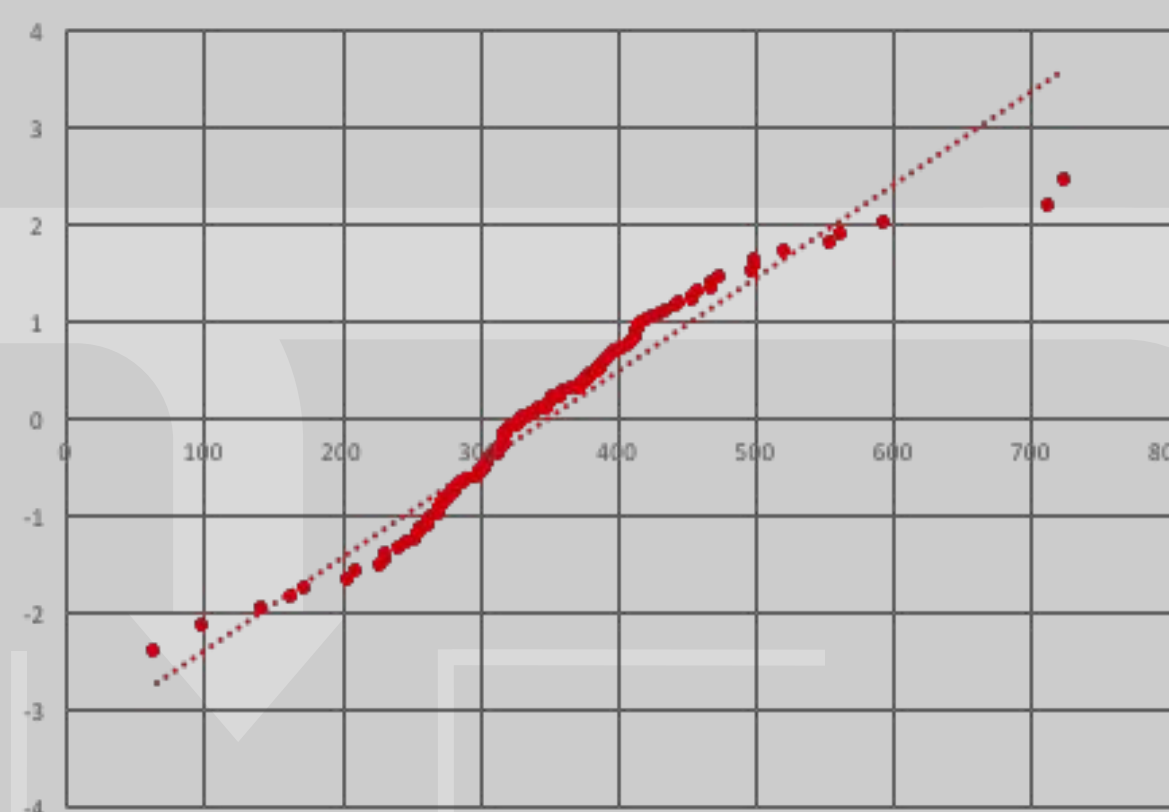
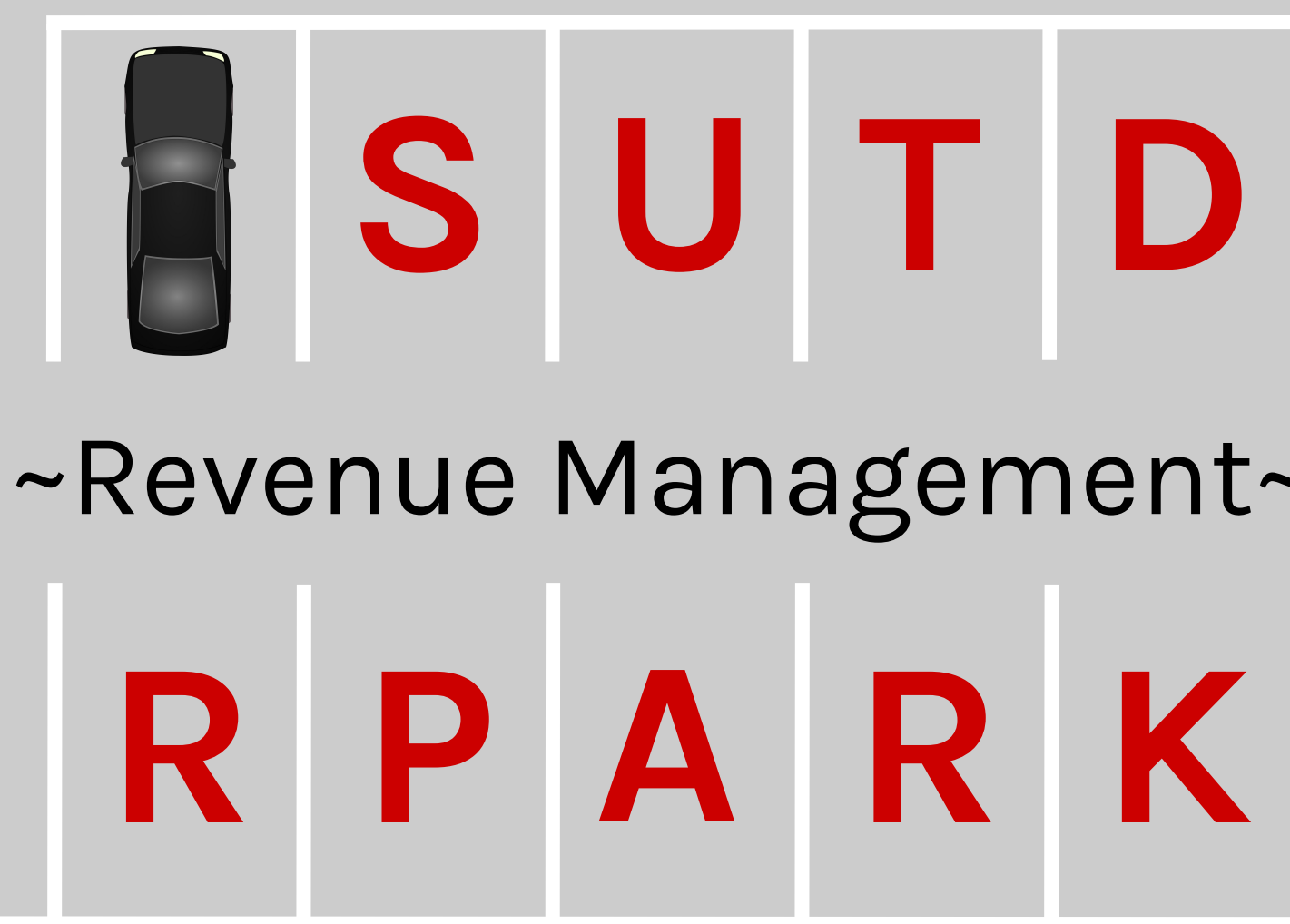
Demand Estimation

The demand for low and high-priced parking was estimated via a variety of means, which included daily summaries and time-study analysis of the carpark. Only the workdays were considered, and a key assumption was that the number of delivery vehicles, motorcyclists and buses was constant for each workday, facilitating the calculation for standard deviation of number of high-paying customers.

$$\begin{aligned} \# \text{ daily entries} &= \# \text{ season parking holders} \times k \\ &+ \# \text{ delivery vehicles} \\ &+ \# \text{ motorcyclists} \\ &+ \# \text{ buses} \\ &+ \# \text{ high-paying drivers} \end{aligned}$$

Analysis of demand

season parking holders ≈ 90 , $k \approx 1.5$
Mean of # high-paying drivers ≈ 200
Standard Deviation of # high-paying drivers ≈ 98



Q-Q plot of the number of high-paying drivers against a standard normal distribution is approximately linear. To verify if the number of high-paying drivers can be modelled as a **Normal random variable**, a goodness-of-fit test was conducted. The Chi-square statistic of 10.8 was smaller than the critical value of 16.0 at $\alpha = 0.1$, thus supporting the use of a Normal random variable to model the number of high-paying customers.

Fitting with $N(\mu=200, \sigma=98)$

Demand	Observed	Expected
0 - 50	5	8.06
50 - 100	7	11.63
100 - 140	20	14.9
140 - 180	29	19.07
180 - 220	17	20.68
220 - 260	22	19.07
260 - 300	13	14.9
300 - 350	9	11.63
> 350	6	8.06

Revenue Management

With estimates for the demand for season parking and for high-priced parking, the tools of revenue management can be applied to provide the optimal number of parking lots that should be set aside to achieve maximum revenue.

The regression for demand vs price was also used to estimate the number of season parking lots that could be filled solely by the people of SUTD.

Average daily revenue per high-paying driver
= **Expected parking duration (hr)** \times **\$1.60/hr**
= 5 \times \$1.60 = **\$8**

Estimated current daily revenue = **\$1,866.25**
Revenue from base case (selling all lots as season lots for \$90) = **\$1,178.18**

Monthly season parking price (\$)	55	60	70	80	90
% of expected demand for season parking from SUTD	100.0%	88.2%	73.4%	58.5%	40.6%
Expected demand for season parking from SUTD	222	196	163	130	90
Price of season parking per day	2.50	2.73	3.18	3.64	4.09
# lots to reserve for season parking	164	168	175	182	189
Expected number of season parking lots occupied by people of SUTD	164	168	163	130	90
Optimal total revenue assuming all season lots sold	\$1,852.44	\$1,881.07	\$1,937.10	\$1,994.71	\$2,052.35
% improvement from base case assuming all season lots sold	57.23%	59.66%	64.41%	69.30%	74.20%
Expected total revenue assuming season parking only for people of SUTD	\$1,852.44	\$1,881.07	\$1,898.92	\$1,801.98	\$1,647.13
% improvement from base case assuming season parking only for people of SUTD	57.23%	59.66%	61.17%	52.95%	39.82%

Conclusion

The analysis for the revenue brings about an interesting insight. With a higher season parking price, more lots should be set aside for season parking in order to maximize revenue, yet if the season parking lots are to be reserved solely for the people of SUTD, then it may be better to set a lower price instead so that more people would be willing to sign up for season parking and thus provide more revenue for the carpark operator.

Limiting Factors

The main limiting factor in the analysis was in the quality of data obtained. Due to privacy issues, the main source of data was number of entries into the carpark, aggregated only by day. As such, the actual demand from high-paying drivers had to be estimated based on a limited time study of the carpark.

Due to limitations of the chosen survey platform, we were unable to obtain demand data for more than 3 price points, as such the accuracy of the regression may be affected by the low number of price points.