# STRUCTURAL ESTIMATIONS OF PRICE - OCCUPANCY RELATIONSHIP IN URBAN PARKING SYSTEMS

by

Adarsh Muraleedharan

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Approved by:

______________________________
Dr. Qiao-Chu "Tony" He

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Dr. Tiantian Nie

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Dr. Gabriel Lopez Zenarosa

# ABSTRACT

ADARSH MURALEEDHARAN. Structural estimations of price - occupancy relationship in urban parking systems. (Under the direction of Dr. QIAO-CHU HE)

Parking is a significant facet of the urban transportation system, with a collective revenue of nearly $30 billion in the United States by the end of 2018. Motivated by the inter-temporal demand and supply imbalance as well as the sub-optimal parking resources utilization in practice, we investigate the structural estimation of the price-occupancy relationship in an urban parking system.

In this study, a series of statistical models and variable selection techniques are proposed or implemented which consist of various spatiotemporal variables using the open data set from SFpark as well as API from our industry partner. The parking prices have been updated in response to the change in parking occupancies across a duration of 18 months, which serves as a natural experiment for price-occupancy estimation. A two-step spatiotemporal estimation procedure is adopted to capture the cross-price effects (incentive externalities) and the time effects, wherein variable selection techniques are employed to regulate over-fitting at each estimation step.

Our study sheds interesting light on the parking price-occupancy relationship. Firstly, we find that the cross-price elasticity of the streets within a neighborhood can form a significant incentive gradient to induce flexible parking behaviors. Secondly, our results show that the spatial variables play an important role in determining the street occupancy (demand). Also, the drivers tend to avoid the streets with the highest parking rate by considering the neighboring cheaper alternatives. The converse is true sometimes at night or on weekends, as the drivers are relatively insensitive to the upper parking prices therein.

Our research is a first step to understand the incentive-driven parking behaviors, which provides the empirical evidence to support parking pricing, operations and eventually infrastructure planning decisions to the policy-makers.

# ACKNOWLEDGMENTS

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To my wonderful parents and my brother, thank you for being the light of my life!

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# DEDICATION

To my late grandparents K.S Siva Raman & Parvathy for the eternal guidance. I have no words to express my gratitude for making me who I am today.

To my late old companion, Tippu. Thank you for all the wonderful childhood memories.

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# CHAPTER 1: INTRODUCTION

According to an analysis by Frost & Sullivan, “Parking industry is expected to attract $200-$250 million of strategic investment over the next 3–5 years in the USA alone.” However, the high demand for parking spaces and the low supply of parking locations, make parking an essential field of study. The City government could make a significant impact on the economy by the optimized utilization of parking resources and by introducing smart parking programs to eliminate supply imbalance.

Searching for a parking spot is hectic, especially for US drivers in major cities. It has been surveyed that motorists spend around 107 hours (more than four days) a year looking for parking. In monetary terms, according to the analysis by INRIX in the city of New York, a driver spends around $2,243 per year in wasted time, fuel, and emissions. Overpaying is another issue, as the drivers pay more than required as they are unaware of the estimated time of parking and thus end up paying more than needed for fear of a parking ticket. Nearly 63% of the total 6000 drivers surveyed avoid going to shopping sites, airports, leisure or sports centers, and other destinations in the urban areas because of inadequate parking spaces and the high cost of parking. On street parking degrades the quality of urban places and generates heavy traffic. Heavy traffic is not only because of the cars which are parked on the road but also because of the cars cruising in search of parking spaces. It is estimated that approximately 30% of the cars cruising in busy cities are looking for parking spots (Shoup, (2006)).

One of the leading causes of the parking anxiety is inadequate parking spaces during the rush hours and the high demand areas. Major cities like New York, Los Angeles, Washington D.C. and San Francisco are the focal points of this kind of situation. Even though there are a lot of new automatic parking technologies such as Aisle, Tower Car Parking Lifts, Puzzle and Car Stacker, technology advances in parking can be complemented by the improved operational management of the existing facilities and spaces, which can be more cost-effective and low hanging fruits.

Recent advancement in technologies and introduction of smart parking programs made the Garage owners and municipalities to have a collective overlook of the available resource and the pricing constraints. Some new companies like Smarking and NuPark are big players in the parking analytics industry. They make use of parking service providers' pricing strategies and historic parking data to make predictions of parking trend in a specific location at a particular time. Thus, it is very important to have a proper pricing strategy which helps in deciding the right price for an on-street parking spot.

Understanding the behavior of parking data is the first step towards this goal. In this research, we investigate the relationship between price and occupancy in urban parking systems. The City of San Francisco is featuring in this paper. The data of 194 streets in the San Francisco Bay area required for the research has been obtained from SFpark (Meter rate adjustment spreadsheet, June 2016) as well as API from our industry partner. SFpark is a demand responsive parking system generated by the municipality of San Francisco.

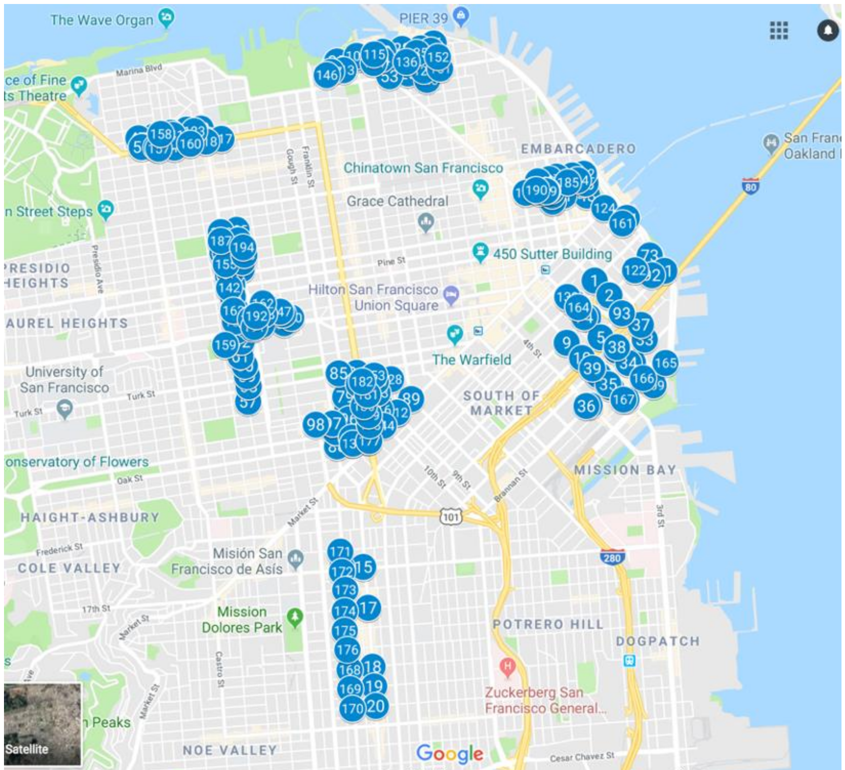


Figure 1: Streets featuring in this research (source: Google Maps).

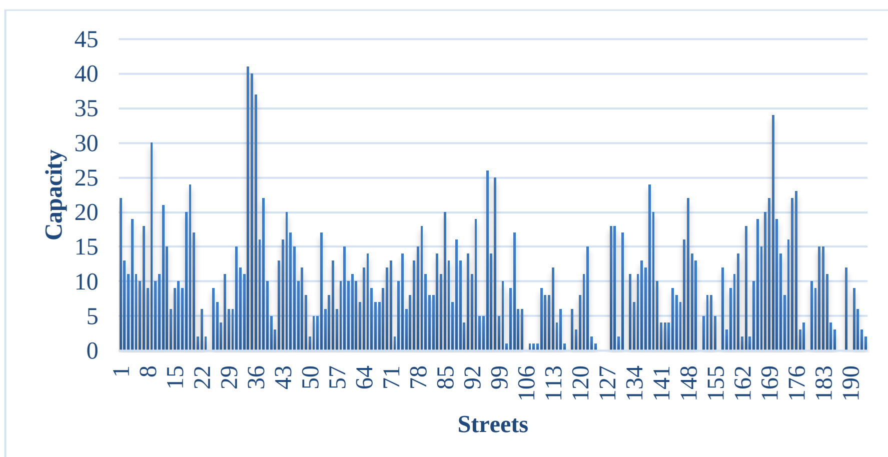


Figure 2: Maximum capacity of streets mentioned above in the map.

In Figure 1, 194 streets in the San Francisco Bay area, which we use in this study are shown with the help of Google maps. Figure 2 shows the maximum capacity of all the 194 streets.

In Chapter 2, we cover literature review on the topic. Chapter 3 explains various linear regression techniques. In Chapter 4, spatiotemporal models are proposed however with no cross effect. In Chapter 5, we propose a model which is an extension of the spatiotemporal model, yet with cross-price effect.

***Nomenclature:***

*Occupancy:* The percentage of capacity of the street parking which is occupied at a given point in time. In other words, Parking demand.

*Price elasticity of Occupancy:* Two types of price elasticities of occupancy are discussed in this paper.

(i) Price elasticity: Percent Change in the occupancy of a street with respect to percent change in its own pricing.

(ii) Cross price elasticity: Percent Change in the occupancy of a street with respect to percent change in pricing of neighboring streets.

# CHAPTER 2: LITERATURE REVIEW

SFpark is a system generated by San Francisco Municipality to manage the availability of street parking. SFpark works by adjusting meter and garage pricing up and down to match demand periodically. This demand-responsive pricing system helps the driver to find open parking spots faster as the driver becomes aware of underused areas and garages and thus reducing demand in overused streets. More information regarding SFpark is available at http://sfpark.org/resource-type/data/. The open data available from SFpark has been used in this research.

In Qian and Rajagopal (2014), to manage parking demand, a new pricing strategy is proposed which is dependent on real-time sensing. Demand uncertainties and user heterogeneity in Value of Time (VoT) are collected over real time and then analyzed to provide the user with all the parking information to make real-time parking choices. This study stands close to our research in analyzing parking behaviors and pricing trends. In a similar study, Daniel Mackowski, Yun Bai and Yanfeng Ouyang (2015) explains the challenges in reducing vehicle circling and maximizing parking space utilization. They propose a dynamic non-cooperative bi-level model (i.e., Stackelberg leader-follower game) to set the parking rates based on real-time data. We try to learn more about the model as this helps in establishing a relationship between price and demand. Millard-Ball, A., R. Weinberger, and R. Hampshire (2013) have discussed the massive effects of parking price changes on driver behavior. They used it to demonstrate the elasticities mentioned in the paper. They have concluded, the drivers do not care about the 25-cent change in parking rate according to demand. But in the longer term, there is a chance of converse happening because of the increased awareness of cumulative rate changes mounting up.

Richard Arnott and Eren Inci (2006), proposes a new downtown parking model that integrates traffic congestion and saturated on-street parking. Authors assume that the cars cruising for parking add to the congestion in traffic. They have observed a robust result which states, “whether or not the amount of on-street parking is optimal, it is efficient to raise the on-street parking fee to the point where cruising for parking is eliminated without parking becoming unsaturated”. This paper helps us in learning more about congestion.

Dadi Baldur Ottosson, Cynthia Chen, Tingting Wang and Haiyun Lin (2013) investigate the sensitivity of on-street parking. The study is based on automatic transaction of data from parking pay stations obtained before and after a parking rate change in Seattle in 2011. This is similar to SFpark’s approach of performance-based pricing. They have worked on the price-elasticity of on-street parking demand which is modified by time of the day and spatial features. Apart from this, the study sheds light on the impact of the change in pricing rates on in parking turnover rates, parking duration and total revenue generated.

Donald Shoup (2005) discusses the problems of typical urban planning technique. The author talks about the planners setting minimum parking requirements to meet the peak demand without considering the price, drivers pay for the parking and the cost of setting up and providing the required parking spaces. Further, the author insists on eliminating minimum parking requirements as that would reduce the cost of urban development, improve urban design and reduce automobile dependency. Donald Shoup (2006) proposes a model of the decisions a driver make while parking the car, as the driver has the choice of parking either in the high demand – low-cost curb parking or in the low demand- high-cost garage parking. Guangzheng Yao, Hongwei Guo, Chunyan Li, Hairui Sun (2016), has done an empirical study which focuses on the factors relevant to vehicle ownership and feasibility of existing parking policy in Beijing. The study shows that family income, family size, geographic location, and parking fee determine the vehicle ownership and thus the parking demand. This helped us in determining the spatial variables. In another case study in China, Qian Liu, James Wang, Peng Chen, Zuopeng Xiao (2016), examine the effects of the built environment on car commuting. Authors conclude that it is wise to impose parking caps in dense and central areas as it hinders parking oversupply.

Edward Calthrop, Stef Proost, Kurt van Dender (2000), talks about the possibilities of trying various combinations of imperfect road-pricing systems and imperfect parking charges. Josvan Ommeren, Derk Wentink, Jasper Dekkers (2009) empirically examines the resident's willingness to pay for on-street parking permits in comparison to cost of cruising.

# CHAPTER 3: LINEAR REGRESSION

Linear Regression is one of the simplest approaches for modeling a relationship between a scalar dependent variable and one or more explanatory variables or independent variables. Most of the new statistical learning methods are based on or extension of the linear regression.

### *3.1: Simple Linear Regression*

Simple Linear Regression is a straight forward approach to explain the response variable $O_i\,[t]$ by the observing and analyzing changes in the predictor variable $X_i[t]$.We are regressing $O_i\,[t]$ onto $X_i[t]$.

Equation 1 expresses a simple linear regression model which represents the relationship between occupancy and parking rate in one of the streets chosen out of the 194 streets.

$$O_i\,[t] = \beta_0[t] + \beta_i X_i[t] \; + \varepsilon_i[t] \tag{1}$$

Where

$O_i\,[t]$ (response variable) represents the occupancy of street i at time t.

$X_i[t]$ (predictor variable) represents the pricing of street i at time t.

$\beta_0[t]$ is the intercept of the model at time t.

$\beta_i$ represents the coefficient of the pricing or the parking rate of street i at time t.

$\varepsilon_i[t]$ is the error or noise associated with the Normal/Gaussian distribution of street i at time t.

A street named “400 Second Street” is chosen out of the 194 streets considered for the study. We will be using the same street throughout the study, to determine the effect of spatiotemporal variables on the occupancy of “400 Second Street,” when we assess the model on a local scale. In the following sections, we estimate the coefficients associated with the model and the closeness of the fit (in other words, the accuracy of the coefficient estimates).

### *3.1.1 Estimating the Coefficients*

In Figure 3, occupancy of "400 Second Street" is plotted with pricing over time. The scattered points have a downward trend, which shows parking demand decreases with increase in pricing.

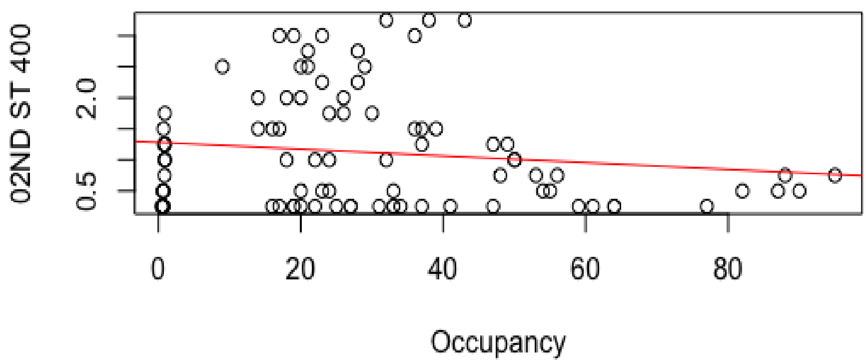


Figure 3: Simple linear regression fit.

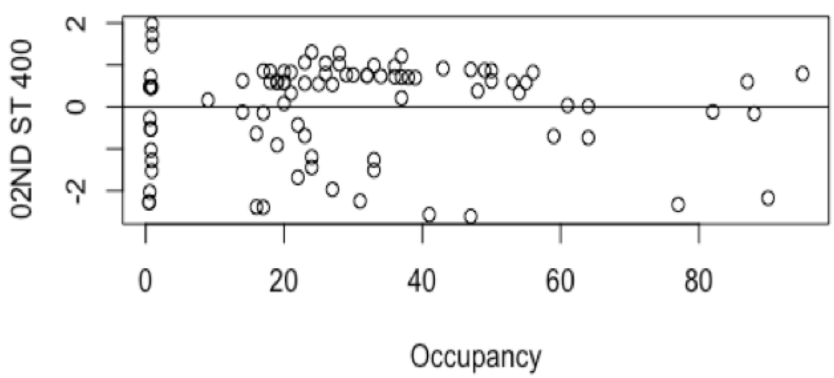


Figure 4: Residuals of the simple linear regression model.

In Figure 4, we analyze residuals of the fit with occupancy. Even though we expect the residuals to be white noise, there is a clear trend in the plot of scattered points and thus establishes the presence of hidden information within the residual.

Table 1: Coefficients of the simple linear regression model.

| | Estimate | Error | t value | Pr(>\|t\|) | |
|---|---|---|---|---|---|
| (Intercept) | 55.903 | 3.462 | 16.149 | <2e-16 | *** |
| `02ND ST 400` | -6.537 | 2.393 | -2.732 | 0.0076 | ** |

### *3.1.2 Assessing the accuracy of the coefficient estimates*

Table 2: Error statistics of the simple linear regression model.

| | |
|---|---|
| Multiple R-squared: 0.07819 | Adjusted R-squared: 0.06772 |
| F-statistic: 7.465 | p-value: 0.007604 |

From Table 1, a negative $\beta_i$ with a p-value close to zero for the model indicates there is an inverse relationship between occupancy and parking rate: parking occupancy decreases in the parking rate. t value represents the results of T statistic tests. T statistics is expressed as the ratio of the deviation of the estimated value of a parameter from its hypothesized value to its standard error. Pr(>|t|) represents the p-value or the significance level of the t statistics of the variables. *** represents the highest significance of the variable in defining the model. F statistic is used to determine whether the model has significant predictive capability. However, since we are focusing more on the regression coefficients at this phase, we ignore F-statistic.

However, this model cannot be used to determine the accuracy of the relationship due to a low $R^2$ value (0.07819), as shown in Table 2. $R^2$ value has been used to measure the goodness of fit. $R^2$ value ranges from 0 to 1. If the $R^2$ value is close to 0, it is a poor fit, and if it is close to 1, it is a good fit. If the number of predictors is large, $R^2$ value keeps on increasing, and thus the model will overfit to the data which makes it useless for forecast because of high flexibility.

However, in this case, we have the $R^2$ value close to zero, which indicates the presence of an unexplained noise which calls for the identifications of additional factors. This concludes that the simple linear regression could not explain, much of the variability in the response. Unexplained variability in the response may be because the error rate is quite high, which demands the need to include more predictors to express the relationship better. As expected, all the streets have shown a linear association with a negative coefficient ($\beta_i$) indicating the occupancy has an inverse association with pricing. Error diagnostics help in determining if there is any unexploited data which can affect $O_i\,[t]$ other than $X_i[t]$.

***3.2: Multiple Linear Regression***

A multiple linear regression model can be expressed as Equation 2. Here Y is the response variable and $X_1, X_2, X_3, X_4 \ldots X_n$ represent predictor variables which we use for regression against Y.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon \tag{2}$$

The variables $X_1, X_2, X_3, X_4 \ldots X_n$ can be from quantitative inputs, transformations of the quantitative inputs, dummy variables and interaction variables.

Dummy coding or numeric coding on variables is done on levels of qualitative inputs. In this case, we have six-time zones indicating three each from weekdays and weekends. The quantitative inputs are the spatiotemporal variables associated with the streets.

We estimate coefficient β from the training data. This is effective only if the training observations are randomly picked and represent the population.

We describe some implicit assumptions based on a multiple linear regression model shown in equation 2. Additive assumption implies the effect of the change in one of the predictors on the response is independent of the values of the other predictors. And linear assumption means that the change in the parking demand with respect to the change in the unit value of the parking rate is constant, irrespective of the value of the parking rate.

As discussed in the last section, a single predictor variable $X_i[t]$ cannot accurately predict the response variable $O_i\,[t]$. We have used various spatiotemporal variables in the following chapters to determine the accuracy of the fit. However, in this section, we introduce inter-temporal effect and time dummies.

In Figure 5. We see the neighborhood of "400 Second Street". All the neighboring streets to "400 Second Street" are marked as black dots and are numbered from 2 to 7. Black dot 1 represents "400 Second Street" itself. Restaurants, gym, gallery, FedEx office, and other services in the neighborhood fall into the category of spatial variables. Dummy variables capture the time zone effect on the occupancy.

To incorporate the effect of time and type of the day of the week, we have introduced dummy variables into the model. Dummy variables are represented by Time1, Time2, …. Time5. Each Time slot has values represented by either 1 or 0. We have used only five dummy variables in the model as there are only six time-slots per day.

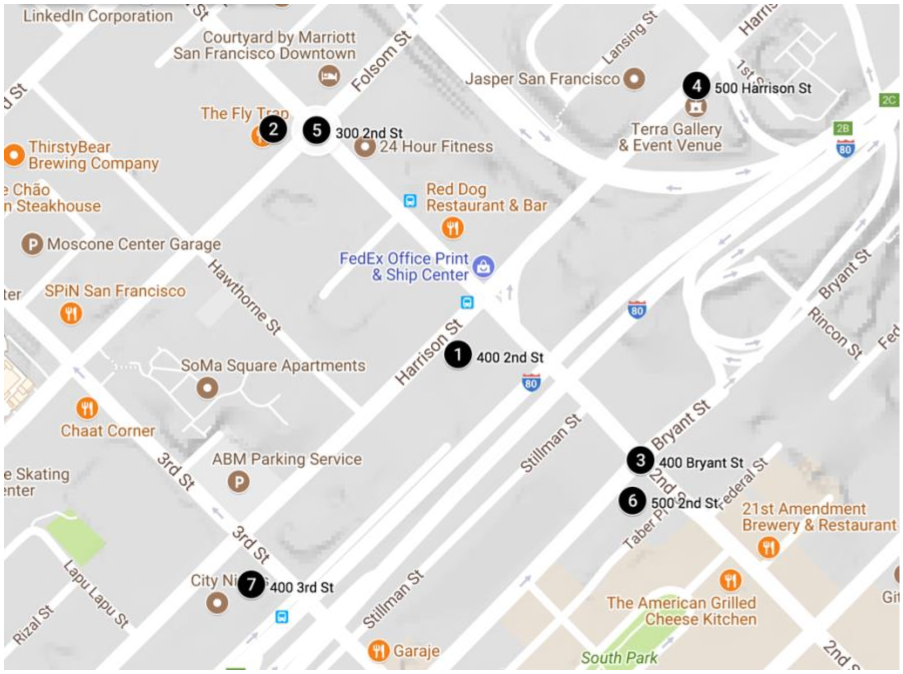


Figure 5: Neighborhood of 400 Second Street (credits: Google Maps )

Time of the day has a very crucial role in determining occupancy as well. For e.g., the morning hours are hectic whereas late night parking is comparatively easier. We observe same trend during weekday/weekend, as the parking rate variation is apparent, and so is the occupancy.

After considering all the temporal variables as well dummy variables, we formulate the model as,

$$O_i[t] = \alpha_i[t] + \beta_i X_i[t] + \sum_{j \neq i} \beta_{ij} X_j[t] + \sum_{n=1}^{5} \delta_i^n I_n[t] + \varepsilon_i[t] \qquad (3)$$

$X_j[t]$ represents the pricing of neighboring streets at time t, where $j \neq i$.

$\beta_{ij}$ is the coefficient of the temporal variables which represents the cross-price elasticity of parking demand within the neighborhood.

$\delta_i^n$ is the coefficient of time dummy at time zone n of street i.

$I_n[t]$ is the time dummy.

*n* represents the integer which denotes the time effect. (1,2,3) represents 9AM-12PM, 12-3PM, 3PM-close respectively on a weekday. (4,5) represents 9AM-12PM and 12-3PM of weekends respectively.

"400 Second Street" is used in this section as well to maintain consistency and for better evaluation of the impact of the temporal and dummy variables used in this module. Figure.5 shows the neighborhood of "400 Second Street." It shows all the nearby shops, streets, and facilities to the "400 Second Street." In this section, we analyze the effect of parking rates of neighboring streets on the occupancy of "400 Second Street."

### *3.2.1 Estimating the coefficients*

Table 3 explains the price elasticity of streets concerning parking demand, within the neighborhood.

Table 3: Coefficients of the multiple linear regression models.

| | 02ND ST 300 | 02ND ST 400 | 02ND ST 500 | 03RD ST 400 | FOLSOM ST 600 | BRYANT ST 400 | HARRISON ST 500 |
|---|---|---|---|---|---|---|---|
| 02ND ST 300 | 2.9693 | 2.192 | -21.7544 | -19.032 | -0.9481 | 2.4693 | 35.3276 |
| 02ND ST 400 | 1.496 | -28.6284 | -9.847 | -6.275 | -7.388 | 13.129 | -9.728 |
| 02ND ST 500 | 23.394 | -22.523 | -1.669 | 29.072 | -14.034 | -6.716 | 48.71 |
| 03RD ST 400 | 25.908 | -3.887 | -3.268 | -15.81 | -17.609 | -32.827 | 41.134 |
| FOLSOM ST 600 | 5.686 | -23.021 | 11.255 | -23.667 | -6.76 | -9.239 | 46.823 |
| BRYANT ST 400 | 12.586 | -11.885 | -2.352 | -22.908 | -4.544 | -12.219 | 38.951 |
| HARRISON ST 500 | 12.112 | -5.103 | -4.173 | -18.178 | -5.917 | -6.741 | -20.937 |

As expected the own price elasticity ($\beta_i$) of parking demand is negative, which is shown along the diagonal. A negative coefficient indicates an inverse association with the parking demand and the parking rate of the respective street. In other words, the sensitivity of the parking demand on the parking rate of the street is high.

Upon analyzing cross-price elasticity ($\beta_{ij}$) in the case of "400 Second Street," explained in row 2 of Table 3, "400 Bryant Street" has a very high positive coefficient. This indicates an increase in parking rate of "400 Bryant Street" makes more drivers switch to "400 Second Street" for parking. All these streets are within a half-mile radius and thus the drivers won't mind walking a bit if there is a significant difference in parking rate in "400 Second Street." The rest of the table can be explained using the same concept. Next section illustrates the accuracy of the model.

### *3.2.2 Assessing the accuracy of the coefficient estimates*

Table 4: Error statistics of the multiple linear regression model.

| | |
|---|---|
| Multiple R-squared: 0.4155, | Adjusted R-squared: 0.3244 |
| F-statistic: 4.561 | p-value: 1.607e-05 |

$R^2$ value has been used in this case as well as to measure the goodness of fit. As shown in Table 4, $R^2$ value has increased significantly compared to the simple linear regression model. This increase indicates that the model is far superior in explaining the relationship between occupancy and parking rates compared to the simple linear regression model. P-value of the model, as well as the coefficients in the model, is close to zero indicating their significance.

Even though we have achieved a significant increase in the $R^2$ value of the regression model, there is a vast scope of improvement as the $R^2$ value is not anywhere close to 1. We have discussed only the temporal variables (related to chronological time) in this chapter. In the next chapter, we introduce spatial variables also into the model as we expect them to play a significant role in defining the price-occupancy relationship.

# CHAPTER 4: SPATIO-TEMPORAL MODELS

In the previous chapter, we discussed how temporal variables could have an impact in determining the occupancy of streets. However, in reality, occupancy is determined by not only temporal variables. For e.g., will the occupancy of the street change if the government decides to build a shopping center or a park in the neighborhood? Will the occupancy of the street changes in the early morning if a new gym is opened in the region? We are introducing spatial variables in this chapter. More detailed explanation of the types and characteristics of spatial variables used in this study is given in the appendix of the dissertation.

Equation 4 expresses the regression model we will be using in this chapter.

$$O_i[t] = \alpha_i[t] + \beta_i X_i[t] + \Sigma_{n=1}^{5} \sum_{p=1}^{P} \gamma^{n,p} Y_i^p + \sum_{n=1}^{5} \delta_i^n I_n[t] + \varepsilon_i[t] \tag{4}$$

$Y_i^p$ indicates the spatial variables corresponding to the street i with respect to the $p^{th}$ spatial predictor.

$\gamma^{n,p}$ is the coefficient of the $p^{th}$ spatial variable at time zone $n$. $\gamma^{n,p}$ captures the interaction between spatial factors with time zone dummies (n).

### *4.1 Two-step method*

We analyze the same street ("400 Second Street") and neighborhood for study in this case as well. We have seen in the first model that the price elasticity of occupancy of a street is high when compared to its pricing. However, there was some data remained to be extracted out of the residual. Thus, we divide the whole regression process into two steps. In the first step, occupancy and pricing of the representative street are analyzed using regression technique. In the second stage, we used the residuals of the first stage as the response variable for the second phase and examined with the spatial variables as the predictors. However, we don't use all the 45 spatial variables listed in the appendix. We use various variable selection techniques to identify the significant spatial variables. Linear model selection and regularization using lasso are explained in detail in the next section. We use this principle for the rest of the study.

### *4.2 Linear model selection and regularization*

Subset selection identifies the best predictor variables from a pool of available predictors. The best model is chosen by combination of various criteria such as Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The model selection can be either done using the best subset algorithm or stepwise selection algorithm. If the number of predictors is huge, using the Best subset algorithm is time-consuming as the computational period for analyzing all the possible combinations ($2^p$) is challenging. Thus, in this case, we use the stepwise selection algorithm to find the best potential predictors which are significant to the response variable (Occupancy).

Stepwise selection is done by either the forward, backward or hybrid approach. In the forward stepwise selection, the regression model starts with zero predictors and then keeps on adding predictors one by one to the model. The predictors which cause any additional improvement are kept in the model, and the rest of the variables are discarded. However, in the case of backward selection technique, the model starts with the model having all the p predictors and then removing one by one if they don't provide any additional improvements to the model by analyzing the RSS value. In the hybrid approach, the variables are added one by one and removed as well by considering the importance of that variable after the new variable is added.

The next method to find the best predictors from the p predictors is through shrinkage. The variance drops significantly once the coefficient estimates are brought down to zero. Shrinkage is done commonly via Ridge regression and Lasso regression. Both these techniques make use of a tuning parameter ($\lambda$) to define the shrinkage penalty. When $\lambda$ is zero, there is no penalty term, and the results will be similar to least square estimate. But Ridge regression makes use of all the predictors in the model except only when the tuning parameter $\{\lambda\} \rightarrow \infty$. This causes the interpretation of the model a bit fuzzy as the number of p is large. Lasso is chosen over ridge for regularization, as ridge regression was not giving proper results. We work on a variety of tuning parameter ($\lambda$) values to find the best fit. In the following section, we work on a case study, where we see the application of two-step method, linear model selection, and regularization.

***4.3 Case study:***

We have 45 spatial predictors and 194 streets used in this study. However, as we look closely at Figure.1, these streets are way apart. Thus, the effect of pricing of a street, miles away from the representative street is negligible and illogical (even if any). E.g., During summer, people go to the beach, when people come to the beach they buy ice cream. Thus, ice cream sale is positively related to the number of people on the beach. However, when people come to the beach, the probability of attacks by sharks also increase. But the shark attack has no relation to the ice cream sales. Thus, in the parking scenario, even if the numbers show some relationship between occupancy and parking rates of streets which are miles apart, that is illogical.

Thus, we pick one street out of the 194 streets and analyze with the neighboring streets by considering the spatial features as well. For consistency, we use “400 Second Street” in this model as well. That helps us to determine the change in the closeness of fit once we introduce cross-price elasticity to the spatiotemporal model. We can use the same model in any other locality of the 194 streets if the temporal and spatial variables are available. In this case study, we work on the neighborhood of "400 Second street." An attempt to work on the 194 streets has been made as well but didn't find much success due to the conflicting spatial variables. Moreover, there is no logic in analyzing streets which are far apart as the potential customers will be totally different at a time. We introduce two-step method in this case study. We carry on the same technique in future models as well.

### *4.3.1 Step 1*

By following Equation 5, all the streets in the neighborhood are analyzed with their pricing along with time dummies in the first step.

Equation 5 expresses the statistical model for the first step of the process.

$$O_i[t] = \alpha_i[t] + \beta_i X_i[t] + \sum_{n=1}^{5} \delta_i^n I_n[t] + E_i[t] \tag{5}$$

$E_i[t]$ is the error or noise associated with the Normal/Gaussian distribution of street i at time t and time zone n.

Table 5: Coefficients of the first step of the spatiotemporal model.

| | Estimate | Std. Error | t value | Pr (>\|t\|) | |
|---|---|---|---|---|---|
| (Intercept) | 45.2637 | 1.965 | 23.035 | < 2e-16 | *** |
| $X_i$ | -1.7846 | 0.5998 | 2.975 | 0.003043 | ** |
| Time1 | 6.944 | 2.3967 | 2.897 | 0.003895 | ** |
| Time2 | 15.1785 | 2.5349 | 5.988 | 3.60E-09 | *** |
| Time3 | 8.9337 | 2.4401 | 3.661 | 0.000272 | *** |
| Time4 | -12.8695 | 2.4159 | -5.327 | 1.40E-07 | *** |
| Time5 | -1.8393 | 2.383 | -0.772 | 0.44051 | |

Table 6: Error statistics of the first step of spatiotemporal model.

| | |
|---|---|
| Multiple R-squared: 0.3145 | Adjusted R-squared: 0.3079 |
| F-statistic: 47.63 | p-value: < 2.2e-16 |

### *4.3.2 Step 2*

In the second step of the model, regression is done on residuals of the first step with the spatial variables in the neighborhood. Variable selection techniques have been applied to the spatial variables to find out the best predictors.

Equation 6 expresses the statistical model for the second step of the process.

$$E_i[t] = \gamma_0[t] + \Sigma_{n=1}^{5} \sum_{p=1}^{P} \gamma^{n,p} Y_i^p + \varepsilon_i[t] \quad (6)$$

$\gamma_0[t]$ is the intercept of the model at time t.

Table 7: Coefficients of the second step of the spatiotemporal model

| | Estimate | Std. Error | t value | Pr(>\|t\|) | |
|---|---|---|---|---|---|
| (Intercept) | -7.48E+00 | 1.04E+00 | -7.185 | 1.92E-12 | *** |
| Daily Transit rider within quarter mile radius. | -4.38E-05 | 4.94E-06 | -8.871 | < 2e-16 | *** |
| Supermarkets within a quarter mile radius | 1.34E-04 | 1.54E-05 | 8.694 | < 2e-16 | *** |
| Gyms within a quarter mile radius | 9.64E-08 | 1.40E-08 | 6.892 | 1.35E-11 | *** |
| Restaurants within a quarter mile radius | 0.600601 | 0.101984 | 5.889 | 6.33E-09 | *** |
| Estimated violent crime within a quarter mile radius | -0.005939 | 0.1093 | -7.139 | 2.61E-12 | *** |

### *4.3.3 Estimating the coefficients*

From Table 5, a negative $\beta_i$ in the first step indicates a high price elasticity on the demand for parking. In other words, parking demand is significantly influenced by the parking rates of the street.

Moreover, by analyzing the time dummies, we see Time1 to Time3 (indicating weekdays) have a positive coefficient. This concludes that the parking demand is high throughout the day with the maximum demand during 12PM-3PM. However, the converse is true, during weekends with less parking demand throughout the day. The cross-price elasticity and effect of spatial variables can be a possible explanation for this parking behavior.

From Table 7, upon analyzing $\gamma^{n,p}$, we find daily transit riders within quarter mile radius have a negative impact on the parking demand. One possible explanation for this adverse effect can be the abundance of public transportation and cab services in the neighborhood. Moreover, supermarkets, gyms, and restaurants within a quarter mile radius make parking difficult in the area because of the high demand. Restaurants have the most significant impact on the parking demand compared to the other two. This is primarily because of the high density of restaurants as well as public places in the neighborhood. Count of violent crimes makes the area less favorite for the public and thus create a negative impact on the parking.

Table 8: Error statistics of the second step of spatiotemporal model.

| | |
|---|---|
| Multiple R-squared: 0.1253 | Adjusted R-squared: 0.1211 |
| F-statistic: 29.88 | p-value: < 2.2e-16 |

***4.4 Summary of spatiotemporal model***

We have analyzed own-price elasticity of the streets in the first step of the model. From Table 5 we see negative coefficient $(\beta_i)\ of\ X_i[t]$ and thus concluded the presence of high own price elasticity of the parking demand, as the model is assisted by low p-value. Moreover, in the second step of the model, from Table 7, we observe spatial variables with very high significance on the occupancy.

However, by analyzing Table 6 and Table 8, we observe low $R^2$ values of the model. This concludes the presence of unexplained noise in the model. One possible explanation of this behavior is the presence of cross-price elasticity of the parking demand. In the next chapter, we will consider the cross-price elasticity. In addition, we also adjust the estimation procedure to improve the goodness-of-fit.

# CHAPTER 5: SPATIOTEMPORAL MODEL WITH CROSS-PRICE EFFECT

Price elasticity is the most convenient way of measuring the responsiveness of demand with respect to change in price. (source: ECON 101). We noticed that the own-price elasticity of parking demand is mostly negative, suggesting a decrease in demand with an increase in price or vice-versa (*the law of demand*). One of the main factors which determine the price elasticity of demand is the availability of close substitutes. In the parking scenario, we have six other streets in the vicinity of any chosen street. Thus, the price elasticity of demand of a street is determined by the pricing of the neighboring streets as well. In other words, the parking demand of any representative street has a cross-price elasticity with other streets in the neighborhood.

Equation 7 expresses the spatiotemporal model with cross-price effect used for estimation of price-occupancy relationship. We have used all the variables (explained in the previous chapters) in this model together to define a statistical model.

$$O_i^n[t] = \alpha_i^n[t] + \beta_i^n X_i^n[t] + \sum_{j \neq i} \beta_{ij}^n X_j^n[t] + \gamma_0^n[t] + \sum_{p=1}^{P} \gamma^{n,p} Y_i^p + \varepsilon_i^n[t] \qquad (7)$$

$O_i^n[t]$ represents the occupancy of the street i at time t and time zone n.

$X_j^n[t]$ represents the pricing of neighboring streets at time t, where $j \neq i$.

$\beta_{ij}^n$ is the coefficient of the temporal variables which represents the cross-price elasticity of parking demand within the neighborhood.

### *5.1 Procedure*

We use two-step method in this model as well. In the first step of the procedure, we find out the effect of spatial parameters on the occupancy of the streets. Then in the second stage, we use the residuals of the first step for regression with the temporal and dummy variables. We intend to capture all the remaining information from the residual, and at last, with the help of error statistics, we compare this model with all the past models to assess the quality of fit.

### *5.2 Two- step method on the spatiotemporal model with cross-price effect*

#### *5.2.1 Step 1:*

In this step, we analyze only the spatial variables with the occupancy.

$$O_i^n[t] = \gamma_0^n[t] + \sum_{p=1}^{P} \gamma^{n,p} Y_i^p + E_i^n[t] \quad (8)$$

Since we have six timestamps in a day, we analyze the effect of spatial variables on occupancy according to time. However, since we are examining only one street out of 194, we need to use variable selection technique to find out the spatial variables which have an impact on the occupancy. We use forward selection technique and Lasso regression to find out the significant spatial variables.

In the next section, we present the results of the first step after doing the variable selection with the forward variable selection and lasso regression. Spatial variables ($Y_i^p$) that are having significant value (by considering the p-value) of $\gamma^{n,p}$ have found themselves in the table. Table 5 to Table 12, shown below present only the spatial variables related to the neighborhood of “400 Second Street.”

#### 5.2.1.1 Spatial variable selection – Results

Table 9 shows the spatial variable selection results using Lasso regression. Table 10 shows the spatial variable selection results using the forward selection technique. A detailed description of results is available in appendix 2 and appendix 3.

Table 9: Spatial variable selection -Lasso.

| Spatial variable selection- Lasso | | | |
|---|---|---|---|
| **Weekday -Positive** | 9AM-12PM | 12PM-3PM | 3PM-Close |
| **Weekday -Negative** | 9AM-12PM | 12PM-3PM | 3PM-Close |
| **Weekend -Positive** | 9AM-12PM | 12PM-3PM | 3PM-Close |
| **Weekend -Negative** | 9AM-12PM | 12PM-3PM | 3PM-Close |

Table 10: Spatial variable selection -Forward selection technique.

| Spatial variable selection- Forward selection technique | | | |
|---|---|---|---|
| **Weekday -Positive** | 9AM-12PM | 12PM-3PM | 3PM-Close |
| **Weekday -Negative** | 9AM-12PM | 12PM-3PM | 3PM-Close |
| **Weekend -Positive** | 9AM-12PM | 12PM-3PM | 3PM-Close |
| **Weekend -Negative** | 9AM-12PM | 12PM-3PM | 3PM-Close |

During morning and evening hours of the weekdays, we see gyms have a positive influence on parking demand. Restaurants, neighborhood commercial zoning, and residential zoning have a positive impact on the demand irrespective of the time of the day. Moreover, alcohol outlets have a positive influence only during lunchtime. However, daily transit rider count and the presence of schools in the locality have a negative impact on the parking demand. However, during weekends, gyms and restaurants continue to favor the parking demand. Moreover, the presence of supermarket, produce market supports the parking. Whereas, alcohol outlets have a significant impact on parking during late hours of weekends. Estimated count of violent crimes and people with no access to any vehicle have made parking less favorite irrespective of the type of the day.

We use the forward selection method instead of Lasso for a better empirical performance. It is quite evident from the Table 10, spatial variables such as supermarkets and commercial zoning have a positive impact on occupancy whereas variables such as estimated violent crime and the number of auto-repair shops hurt the occupancy.

***5.2.2 Step 2:***

Once we figure out the significant spatial variables in the locality then, we move onto the temporal variables. The residuals of the first regression model are used as the response variable for the regression model in the second step. Now we regress all the temporal variables onto the residuals of the first step.

Equation 9 expresses the statistical model for the second phase of the process.

$$E_i^n[t] = \alpha_i^n[t] + \beta_i^n X_i^n[t] + \sum_{j \neq i} \beta_{ij}^n X_j^n[t] + \varepsilon_i^n[t] \tag{9}$$

Forward variable selection is used to check if the parking rates of neighboring streets (shown as the numbered black dots) in the map are relevant in determining the occupancy of "400 Second Street." All the streets have turned out to be significant and thus we decide to move on with Step 2. As stated earlier, temporal variables $X_i^n[t]$ and $X_j^n[t]$ are regressed onto $E_i^n[t]$. We expect the temporal variables to fit better than the multiple linear regression model explained in chapter 3, as we use a fused data set which incorporates factors from both the dimensions.

#### *5.2.2.1 Estimating the coefficients*

This phase of the process is similar to the multiple linear regression model explained in chapter 3. Table 13 shows cross-price elasticity matrix, which describes the correlation between the occupancy of each street on the pricing of the neighboring streets. This is an updated version of Table 2. The darkness of the red increases with the decrease in value.

Table 11: Coefficients of the spatiotemporal model with cross-price effect.

| | 02ND ST 300 | 02ND ST 400 | 02ND ST 500 | 03RD ST 400 | FOLSOM ST 600 | BRYANT ST 400 | HARRISON ST 500 |
|---|---|---|---|---|---|---|---|
| 02ND ST 300 | -8.3904 | -3.0118 | -21.7544 | 2.2287 | 5.78 | 19.3936 | 5.4299 |
| 02ND ST 400 | 1.6932 | -9.5438 | 7.5158 | 2.3772 | -2.1441 | -6.9756 | 3.5667 |
| 02ND ST 500 | 19.910176 | -1.254405 | -18.887494 | 4.206669 | 1.805981 | 22.871769 | -10.004064 |
| 03RD ST 400 | 13.4458 | 3.5965 | 23.1501 | -18.2644 | 1.4856 | -1.2828 | -14.2333 |
| FOLSOM ST 600 | -0.3854 | 5.1722 | -4.3816 | -2.9041 | -15.2678 | 17.8611 | -2.4886 |
| BRYANT ST 400 | 2.9947 | 11.3895 | -3.4856 | -7.8178 | -11.9851 | 0.2777 | 0.4587 |
| HARRISON ST 500 | -0.9638 | -11.2748 | 12.411 | 11.0762 | 2.4473 | 7.4811 | -23.1058 |

As expected the own price elasticity ($\beta_i^n$) of parking demand is negative, which is shown along the diagonal. A negative coefficient indicates an inverse association with the parking demand and the parking rate of the respective street.

Upon analyzing the cross-price elasticity ($\beta_{ij}^n$) of "400 Second Street," explained in row 2, we have the effect of other streets in the neighborhood. "400 Bryant Street" has a very high positive coefficient indicating an increase in the parking of "400 Bryant Street" makes more drivers switch to "400 Second Street" for parking. All these streets are within a half a mile radius, and thus the drivers won't mind walking a bit if there is a significant difference in parking rate in "400 Second Street". The rest of the table can be explained using the same concept.

### *5.3 Assessing the accuracy of the coefficient estimates*

Table 12: Error statistics of the spatiotemporal model with cross-price effect.

| | |
|---|---|
| Multiple R-squared: 0.7662 | Adjusted R-squared: 0.7297 |
| F-statistic: 21.02 | p-value: < 2.2e-16 |

Compared to all the previous models, $R^2$ value has increased significantly. This indicates that the model is far superior in explaining the relationship between occupancy and parking rates compared to the simple linear regression model. Since F-statistic is significantly higher than other models used to find the relationship. However, the p (number of predictors) is not considerably lesser than n (number of observations), we cannot wholly rely on this parameter. P-value of the model, as well as the coefficients in the model, is close to zero indicating their significance of the parameters used in the model. Residuals of the final model are then analyzed to determine if the residual is white noise.

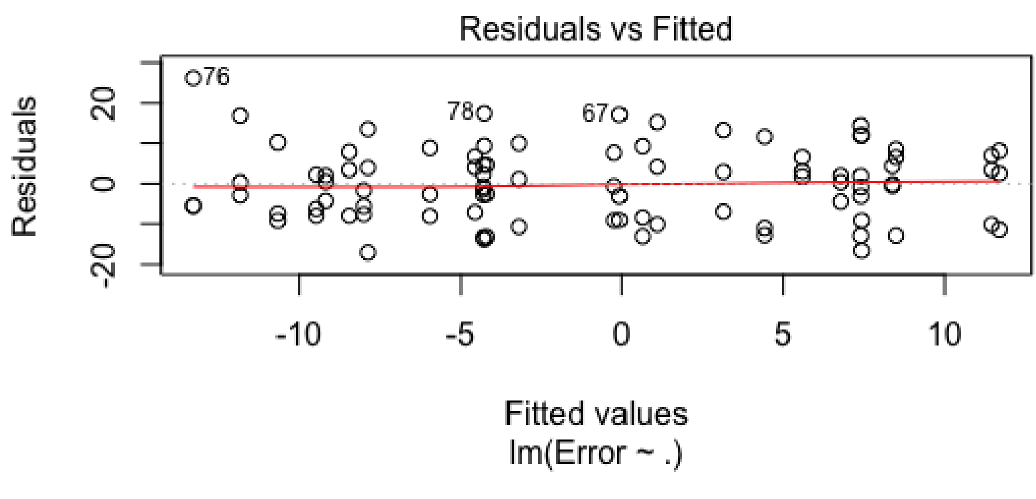


Figure 7: Residuals vs fitted values (Final Model)

Figure 7 shows that residuals of the model are scattered along the space and are hovering around the mean line.

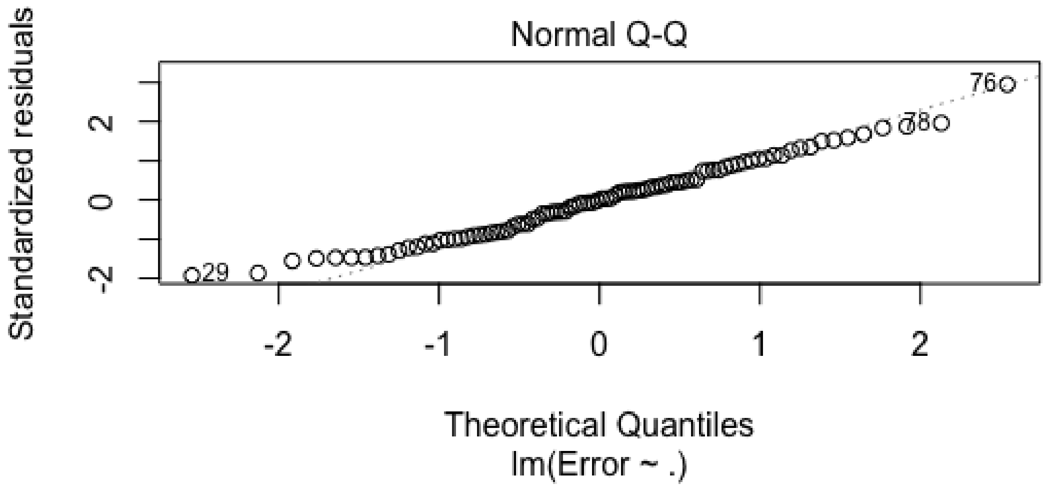


Figure 8: Normal Q-Q plot (Final Model)

The normal Q-Q plot in Figure 8, shows the residuals are following a straight line with only a few data points (such as #29) out of the straight line. This shows residuals are normally distributed.

From Figure7 and 8, we conclude the presence of white noise and the residuals are deprived of any valuable information.

***5.4 Summary of the spatiotemporal model with cross-price effect***

As expected, spatial parameters play a very significant role in determining the parking demand. Using variable selection technique, we find that, restaurants are the primary attraction for parking in the neighborhood irrespective of the time and type of the day. We find that gyms make an impact in parking only in the morning and evening hours. This is very close to reality as people often visit gym during those hours.

In the case of "400-second street," from Table 12, we can see that the cross-price elasticity within the neighborhood is very high. Upon reviewing row 2 of Table 12("400-second street"), we see that "02$^{ND}$ ST 300" has a positive coefficient which denotes an increased parking demand for "02$^{ND}$ ST 300" when the parking rates of "400-second street" is increased. All streets except "BRYANT ST 400" have positive coefficients. This represents the high cross-price elasticity of this streets. "BRYANT ST 400" might be acting as an extension of 02$^{ND}$ ST 400 due to the proximity.

# CHAPTER 6: CONCLUSIONS

In this study, we investigate the structural estimation of the price-occupancy relationship in an urban parking system. We started with a simple linear regression model and finished with a spatiotemporal model with cross-price effect. We find that even though the parking demand of a street depends highly on its pricing, cross-price elasticity of other streets in the neighborhood, as well as spatial variables, play an essential role as well. Time of the day, as well as the day of the week, are crucial factors in determining the price-occupancy relationship.

Since spatial variables play an essential role in occupancy, using 194 streets together in a single model doesn't help in determining the price- occupancy relationship as the potential customers/drivers vary with the neighborhood. Incorporating the time of day effect as a heterogeneity in both observables and explanatory variables, improves the estimation procedure significantly compared with the previous approach by treating them as dummy variables in explanatory factors. Empirical results suggest that the cross-price elasticity is most significant for neighborhood streets. Drivers tend to avoid the streets with the highest parking rate by considering the neighboring cheaper alternatives. The converse is true sometimes at night or on weekends, as the drivers are relatively insensitive to the high parking prices therein. We find that the presence of restaurants and gyms causes an increase in the parking demand in the neighborhood used for the study. However, alcohol outlets produce a positive impact during weekends.

Future work on this topic can be done towards developing more delicate models which incorporates the non-linear relationship and interactions among the spatial variables. Once we establish a proper relationship between parking demand and price, parking demand forecasting can be performed with higher confidence. Moreover, policy recommendation can be provided regarding the optimal demand-responsive parking prices to improve the parking resource allocations.

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# APPENDIX 1: ***Spatial variables***

Some of the important spatial variables along with the factors of them are listed below.

1) Transportation

- Daily Transit rider within quarter mile radius.
- Daily Transit rider within eighth mile radius.

2) Community

- Count of child care facilities within quarter mile radius.
- Count of community centers within quarter mile radius.
- Count of community garden within quarter mile radius.
- Count of libraries within quarter mile radius.
- Count of parks within quarter mile radius.
- Count of post offices within quarter mile radius.

3) Education

- Count of all public/private schools in a quarter mile radius.

4) Business

- Alcohol outlets within a quarter mile radius.
- Auto repair shops within a quarter mile radius.
- Banks within a quarter mile radius.
- Bike shops within a quarter mile radius.
- Dry cleaners within a quarter mile radius.
- Farmers market within a quarter mile radius.
- Gyms within a quarter mile radius.

- Hair salon/ Barber shop within a quarter mile radius.
- Hardware stores within a quarter mile radius.
- Laundromats within a quarter mile radius.
- Produce markets within a quarter mile radius.
- Restaurants within a quarter mile radius.
- Supermarkets within a quarter mile radius.
- Video stores/Theatres within a quarter mile radius.

5) Demographics

- Count of individuals within 200% of poverty line within a quarter mile radius.
- Count of individuals with disabilities within a quarter mile radius.
- Count of estimated employees within a quarter mile radius.
- Count of estimated non-English speakers within a quarter mile radius.
- Count of estimated people of color within a quarter mile radius.
- Estimated residential population within a quarter mile radius.
- Estimated youth less than 18 within a quarter mile radius.
- Estimated violent crime within a quarter mile radius.
- Estimated proportion of people with no vehicle access within a quarter mile radius.
- Proportion of ages less than 13 living within a quarter mile radius.
- Proportion of ages 13-20 living within a quarter mile radius.
- Proportion of ages 21-44 living within a quarter mile radius.
- Proportion of ages 45-64 living within a quarter mile radius.
- Proportion of ages 65+ living within a quarter mile radius.

6) Land use

- Proportion of industrial zoning within a quarter mile radius.
- Proportion of commercial zoning within a quarter mile radius.
- Proportion of mixed use within a quarter mile radius.
- Proportion of Neighborhood commercial zoning within a quarter mile radius.
- Proportion of Residential zoning within a quarter mile radius.
- Proportion of Residential mixed-use zoning within a quarter mile radius.
- Proportion of Redevelopment zoning within a quarter mile radius.
- Proportion of Public use zoning within a quarter mile radius.

Transportation is an important factor as it gives the number of vehicles on the road which affects the occupancy of the streets. Community variables denote the public facilities available in the locality which is proportional to the transport density. Education variable shows the number of schools around the area of the parking space.

Business is one of the most critical variables in the model as it incorporates all the facilities as well as stores which will be crowded throughout the entire day. The average time a customer spends in these facilities is same as the cars being parked in the garage nearby. Alcohol outlets, gyms, farmers market, dry cleaners, bike shops, bank, etc. have an estimated waiting time of 10-60 minutes.

Demographics have also been considered while developing the model as those can affect the density of vehicles around the parking lot. Land use variable represents the zoning type of the neighborhood. Presence of commercial zones and residential zones in the community increases parking demand.

# APPENDIX 2: ***Spatial variable selection - lasso***

Spatial factors with a positive impact on parking demand:

Lasso: Weekday 9AM-12PM

| | |
|---|---|
| 9AM-12PM | Gyms within a quarter mile radius. |
| | Restaurants within a quarter mile radius. |
| | Proportion of ages 45-64 living within a quarter mile radius. |
| | Proportion of neighborhood commercial zoning within a quarter mile radius. |
| | Proportion of residential zoning within a quarter mile radius. |
| | Proportion of residential mixed-use zoning within a quarter mile radius. |

Lasso: Weekday 12PM – 3PM

| | |
|---|---|
| 12PM-3PM | Alcohol outlets within a quarter mile radius. |
| | Restaurants within a quarter mile radius. |
| | Video stores/Theatres within a quarter mile radius. |
| | Proportion of ages 45-64 living within a quarter mile radius. |
| | Proportion of neighborhood commercial zoning within a quarter mile radius. |
| | Proportion of residential zoning within a quarter mile radius. |
| | Proportion of redevelopment zoning within a quarter mile radius. |

Lasso: Weekday 3PM – Close

| | |
|---|---|
| 3PM-Close | Gyms within a quarter mile radius. |
| | Video stores/Theatres within a quarter mile radius. |
| | Banks within a quarter mile radius. |
| | Proportion of ages 45-64 living within a quarter mile radius. |
| | Proportion of neighborhood commercial zoning within a quarter mile radius. |
| | Proportion of residential zoning within a quarter mile radius. |
| | Restaurants within a quarter mile radius. |

Spatial factors with a negative impact on parking demand:

Lasso: Weekday 9AM-12PM

| | |
|---|---|
| 9AM-12PM | Count of all public/private schools in a quarter mile radius. |
| | Proportion of ages 13-20 living within a quarter mile radius. |
| | Proportion of commercial zoning within a quarter mile radius. |
| | Proportion of public use zoning within a quarter mile radius. |
| | Daily transit rider within quarter mile radius. |
| | Daily transit rider within eighth mile radius. |

Lasso: Weekday 12PM – 3PM

| | |
|---|---|
| 12PM-3PM | Count of estimated people of color within a quarter mile radius. |
| | Proportion of ages 13-20 living within a quarter mile radius. |
| | Count of individuals within 200% of poverty line within a quarter mile radius. |
| | Proportion of industrial zoning within a quarter mile radius. |
| | Proportion of public use zoning within a quarter mile radius |

Lasso: Weekday 3PM – Close

| | |
|---|---|
| 3PM-Close | Count of individuals within 200% of poverty line within a quarter mile radius. |
| | Proportion of industrial zoning within a quarter mile radius. |
| | Count of all public/private schools in a quarter mile radius. |
| | Daily transit rider within quarter mile radius. |
| | Daily transit rider within eighth mile radius. |

Spatial factors with a positive impact on parking demand:

Lasso: Weekend 9AM-12PM

| | |
|---|---|
| 9AM-12PM | Bike shops within a quarter mile radius. |
| | Dry cleaners within a quarter mile radius. |
| | Produce markets within a quarter mile radius. |
| | Supermarkets within a quarter mile radius. |
| | Proportion of ages less than 13 living within a quarter mile radius. |
| | Proportion of neighborhood commercial zoning within a quarter mile radius. |
| | Proportion of residential zoning within a quarter mile radius. |

Lasso: Weekend 12PM – 3PM

| | |
|---|---|
| 12PM-3PM | Bike shops within a quarter mile radius. |
| | Produce markets within a quarter mile radius. |
| | Supermarkets within a quarter mile radius. |
| | Proportion of ages less than 13 living within a quarter mile radius. |
| | Hair salon/ Barber shop within a quarter mile radius. |
| | Proportion of neighborhood commercial zoning within a quarter mile radius. |
| | Proportion of residential zoning within a quarter mile radius. |

Lasso: Weekend 3PM – Close

| | |
|---|---|
| 3PM-Close | Alcohol outlets within a quarter mile radius. |
| | Restaurants within a quarter mile radius. |
| | Produce markets within a quarter mile radius. |
| | Supermarkets within a quarter mile radius. |
| | Proportion of ages less than 13 living within a quarter mile radius. |
| | Proportion of ages 13-20 living within a quarter mile radius. |
| | Proportion of ages 65+ living within a quarter mile radius. |
| | Proportion of neighborhood commercial zoning within a quarter mile radius. |
| | Proportion of residential zoning within a quarter mile radius. |

Spatial factors with a negative impact on parking demand:

Lasso: Weekend 9AM-12PM

| | |
|---|---|
| 9AM-12PM | Auto repair shops within a quarter mile radius. |
| | Count of individuals within 200% of poverty line within a quarter mile radius. |
| | Proportion of residential mixed-use zoning within a quarter mile radius. |
| | Proportion of redevelopment zoning within a quarter mile radius. |
| | Proportion of public use zoning within a quarter mile radius. |
| | Count of estimated people of color within a quarter mile radius. |
| | Daily transit rider within quarter mile radius. |
| | Daily transit rider within eighth mile radius. |

Lasso: Weekend 12PM – 3PM

| | |
|---|---|
| 12PM-3PM | Yearly pedestrian volume. |
| | Daily pedestrian volume. |
| | Count of individuals within 200% of poverty line within a quarter mile radius. |
| | Proportion of industrial zoning within a quarter mile radius. |
| | Proportion of residential mixed-use zoning within a quarter mile radius. |
| | Proportion of public use zoning within a quarter mile radius. |
| | Daily transit rider within quarter mile radius. |
| | Daily transit rider within eighth mile radius. |

Lasso: Weekend 3PM – Close

| | |
|---|---|
| 3PM-Close | Yearly pedestrian volume. |
| | Daily pedestrian volume. |
| | Count of estimated people of color within a quarter mile radius. |
| | Count of individuals within 200% of poverty line within a quarter mile radius. |
| | Proportion of residential mixed-use zoning within a quarter mile radius. |
| | Daily transit rider within quarter mile radius. |
| | Daily transit rider within eighth mile radius. |

# APPENDIX 3: ***Spatial variable selection - forward selection***

Spatial factors with a positive impact on parking demand:

Forward selection: Weekday 9AM-12PM

| | |
|---|---|
| 9AM-12PM | Video stores/Theatres within a quarter mile radius. |
| | Gyms within a quarter mile radius. |
| | Restaurants within a quarter mile radius. |
| | Proportion of ages 45-64 living within a quarter mile radius. |
| | Proportion of neighborhood commercial zoning within a quarter mile radius. |
| | Proportion of residential zoning within a quarter mile radius. |
| | Proportion of residential mixed-use zoning within a quarter mile radius. |

Forward selection: Weekday 12PM – 3PM

| | |
|---|---|
| 12PM-3PM | Alcohol outlets within a quarter mile radius. |
| | Restaurants within a quarter mile radius. |
| | Video stores/Theatres within a quarter mile radius. |
| | Proportion of neighborhood commercial zoning within a quarter mile radius. |
| | Proportion of residential zoning within a quarter mile radius. |

Forward selection: Weekday 3PM – Close

| | |
|---|---|
| 3PM-Close | Laundromats within a quarter mile radius. |
| | Average household income within a quarter mile radius. |
| | Video stores/Theatres within a quarter mile radius. |
| | Proportion of residential zoning within a quarter mile radius. |
| | Proportion of neighborhood commercial zoning within a quarter mile radius. |
| | Gyms within a quarter mile radius. |
| | Video stores/Theatres within a quarter mile radius. |
| | Banks within a quarter mile radius. |

Spatial factors with a negative impact on parking demand:

Forward selection: Weekday 9AM-12PM

| | |
|---|---|
| 9AM-12PM | Daily transit rider within quarter mile radius. |
| | Daily transit rider within eighth mile radius. |
| | Produce markets within a quarter mile radius |
| | Count of all public/private schools in a quarter mile radius. |
| | Estimated proportion of people with no vehicle access within a quarter mile radius. |

Forward selection: Weekday 12PM – 3PM

| | |
|---|---|
| 12PM-3PM | Produce markets within a quarter mile radius. |
| | Count of estimated people of color within a quarter mile radius. |
| | Proportion of public use zoning within a quarter mile radius. |
| | Count of individuals within 200% of poverty line within a quarter mile radius. |
| | Estimated proportion of people with no vehicle access within a quarter mile radius. |
| | Daily pedestrian volume. |

Forward selection: Weekday 3PM – Close

| | |
|---|---|
| 3PM-Close | Daily pedestrian volume. |
| | Number of senior centers within quarter mile radius. |
| | Count of all public/private schools in a quarter mile radius. |
| | Count of individuals within 200% of poverty line within a quarter mile radius. |
| | Estimated proportion of people with no vehicle access within a quarter mile radius. |
| | Daily transit rider within quarter mile radius. |
| | Daily transit rider within eighth mile radius. |

Spatial factors with a positive impact on parking demand:

Forward selection: Weekend 9AM-12PM

| | |
|---|---|
| 9AM-12PM | Average household income within a quarter mile radius. |
| | Proportion of ages less than 13 living within a quarter mile radius. |
| | Proportion of neighborhood commercial zoning within a quarter mile radius. |
| | Proportion of residential zoning within a quarter mile radius. |
| | Bike shops within a quarter mile radius. |
| | Dry cleaners within a quarter mile radius. |
| | Produce markets within a quarter mile radius. |
| | Supermarkets within a quarter mile radius. |

Forward selection: Weekend 12PM – 3PM

| | |
|---|---|
| 12PM-3PM | Proportion of ages less than 13 living within a quarter mile radius. |
| | Proportion of ages 13-20 living within a quarter mile radius. |
| | Bike shops within a quarter mile radius. |
| | Produce markets within a quarter mile radius. |
| | Supermarkets within a quarter mile radius. |
| | Proportion of redevelopment zoning within a quarter mile radius. |
| | Hair salon/ Barber shop within a quarter mile radius. |

Forward selection: Weekend 3PM – Close

| | |
|---|---|
| 3PM-Close | Alcohol outlets within a quarter mile radius. |
| | Restaurants within a quarter mile radius. |
| | Produce markets within a quarter mile radius. |
| | Supermarkets within a quarter mile radius. |
| | Estimated proportion of people with no vehicle access within a quarter mile radius. |
| | Proportion of ages less than 13 living within a quarter mile radius. |
| | Proportion of ages 13-20 living within a quarter mile radius. |
| | Proportion of commercial zoning within a quarter mile radius. |
| | Proportion of mixed use within a quarter mile radius. |

Spatial factors with a negative impact on parking demand:

Forward selection: Weekend 9AM-12PM

| | |
|---|---|
| 9AM-12PM | Proportion of ages 21-44 living within a quarter mile radius. |
| | Count of individuals within 200% of poverty line within a quarter mile radius. |
| | Proportion of public use zoning within a quarter mile radius. |
| | Daily transit rider within quarter mile radius. |
| | Daily transit rider within eighth mile radius. |

Forward selection: Weekend 12PM – 3PM

| | |
|---|---|
| 12PM-3PM | Daily transit rider within quarter mile radius. |
| | Daily transit rider within eighth mile radius. |
| | Estimated violent crime within a quarter mile radius. |
| | Count of individuals within 200% of poverty line within a quarter mile radius. |
| | Proportion of residential mixed-use zoning within a quarter mile radius. |
| | Proportion of residential mixed-use zoning within a quarter mile radius. |
| | Proportion of public use zoning within a quarter mile radius. |

Forward selection: Weekend 3PM – Close

| | |
|---|---|
| 3PM-Close | Yearly pedestrian volume. |
| | Daily pedestrian volume. |
| | Count of estimated people of color within a quarter mile radius. |
| | Estimated violent crime within a quarter mile radius. |
| | Count of individuals within 200% of poverty line within a quarter mile radius. |
| | Proportion of residential mixed-use zoning within a quarter mile radius. |
| | Proportion of public use zoning within a quarter mile radius. |
| | Daily transit rider within quarter mile radius. |
| | Daily transit rider within eighth mile radius. |

# VITA

Adarsh Muraleedharan is a graduate student in the University of North Carolina, Charlotte. He was born on June 14th, 1991 in Kerala, India. He obtained an undergraduate degree in mechanical engineering from the University of Kerala, India. After undergraduate studies, he worked with Infosys, a leading IT company in India, for three years. He was in the mechanical engineering research and development wing of Infosys. After three years of corporate life, he resigned from Infosys for higher education. He has joined the University of North Carolina at Charlotte for pursuing Master of Science degree in engineering management with a concentration on logistics and supply chain management.

Apart from studies, Adarsh is a semi-professional chess and badminton player. Moreover, he is fluent in five languages.