Investment opportunities for QuickParking in Milan

November 2023

Prepared by:
Amedeo Filippini
Davide Peluso
Krisina Firsova
Lorenzo Costa

Table of Contents

1. Executive summary

OBJECTIVE

Our goal with this report is to present some **investment opportunities** for the company Quick No Problem Parking around the area of Milan. We accomplished this by first defining precisely the two opportunities (i.e., our theories), collecting data through a survey and then running some analyses to check if our initial assumptions were correct.

THEORY

The goal of the two theories we formulate is to increase profit for the company but with two different approaches.
Our first proposal is to adopt **dynamic prices**. This is based on the analysis of secondary data, coming directly from Quick No Problem Parking, which shows that demand changes depending on two conditions: day of the week and weather conditions. The second proposal is to sell a **bundle of subscriptions** to the parking lot and to a bar nearby.

FINDINGS

Using the data gathered from the survey we realize that **some of our assumptions were wrong**. Indeed, the data revealed that the willingness to pay of clients is influenced by the weather but not the day of the week and that a bundle with a coffee shop does not increase the number of subscriptions. Considering these results of the analysis we **update** the theory incorporating the new information

RECOMMENDATION

In light of all this we recommend management to invest to implement **weather-based pricing** since this can significantly boost revenues. On the contrary a subscription bundle does not seem a good investment opportunity.
Nonetheless we highlight that our findings are not **conclusive**, and that further analysis may be needed to really understand if those two opportunities are worth implementing.

2. Introduction

The Quick Group, founded in 2000 and based in Naples, is a prominent player in **parking management** and **construction services**. It's backed by major shareholders including Fin Posillipo Spa of the Petrone industrial group and the founding Vernetti and Mauro families. The company, with over 250 employees, operates traditional and valet parking services across Italy in more than 60 locations, including airports, ports, and shopping centers. It manages about 40,000 parking spaces and services over 12 million cars annually.

Additionally, Quick Group is a major stakeholder in Napoletana Parcheggi Spa, specializing in parking and mobility solutions, and in Sigea Costruzioni, a leading firm in construction and plant engineering.

Quick Group's success is marked by a substantial share capital of €18,037,000, various quality certifications, and a financial audit certification from PriceWaterhouse&Coopers, reflecting its excellence and leading position in the market.

Considering the strategic objectives and the nature of our organization, we've created a set of theories aimed at **enhancing** the company's **economic performance** and **market positioning**. These theories are structured into two primary categories, each serving a distinct purpose in our business model.

The first theory is centered around the introduction of a **dynamic pricing system**. By adjusting prices based on weather fluctuations and weekly trends, we aim to optimize revenue during peak and off-peak periods, ensuring a balanced and demand-responsive pricing model.

The second is focused on customer loyalty and engagement through the launch of an **exclusive premium subscription service**. This isn't just another subscription model; it's a strategic alliance with local entities such as coffee shops. By bundling our services with those of popular local businesses, we aim to create a symbiotic relationship that enhances the value for our customers and supports local commerce. This premium subscription is designed to offer additional perks thereby cultivating a sense of **exclusivity** and **belonging** among our subscribers.

Both these theories are designed to integrate with Quick No Problem Parking's operations introducing innovative elements that set the company apart in a competitive marketplace.

3. Theory Building

a. First Theory: flexible pricing

Our first theory suggests implementing a **dynamic pricing system** for parking tickets, where fees vary based on weekly trends and weather conditions. Weather conditions would affect pricing by increasing rates during bad weather for the added convenience of closer covered parking. This approach aims to optimize parking space usage and **maximize revenue**.

In the development of our first theory, we drew inspiration from various **articles** and **papers** that discussed situations bearing some similarities to our concept. This idea has parallels with the dynamic pricing phenomenon, a strategy employed across several industries. This approach is notably prevalent in the **airline sector**, but it's also widely utilized by well-known companies like Amazon, Uber, and Airbnb.

Dynamic pricing involves adjusting prices based on **real-time supply** and **demand conditions**. It's a strategy that allows companies to maximize revenue by charging higher prices when demand is strong and lowering them when demand drops. This pricing model has proven effective in various sectors, particularly in those where the **supply is relatively fixed**, and demand fluctuates, like in airline ticketing and hotel bookings.

Interestingly, in the parking industry, this specific policy is very **nearly non-existent**. However, its potential implementation could lead to a significant increase in revenue. By more **efficiently aligning parking availability** and **pricing** with the varying needs of its customers, parking facilities could optimize their usage and profitability.

The first theory is then centered around the idea of introducing **dynamic pricing** for the parking lot based on two factors: the **weather conditions** and the **day of the week**. Our focal attribute is the **revenue** of the company. The structure of our network can be seen on the graph below:

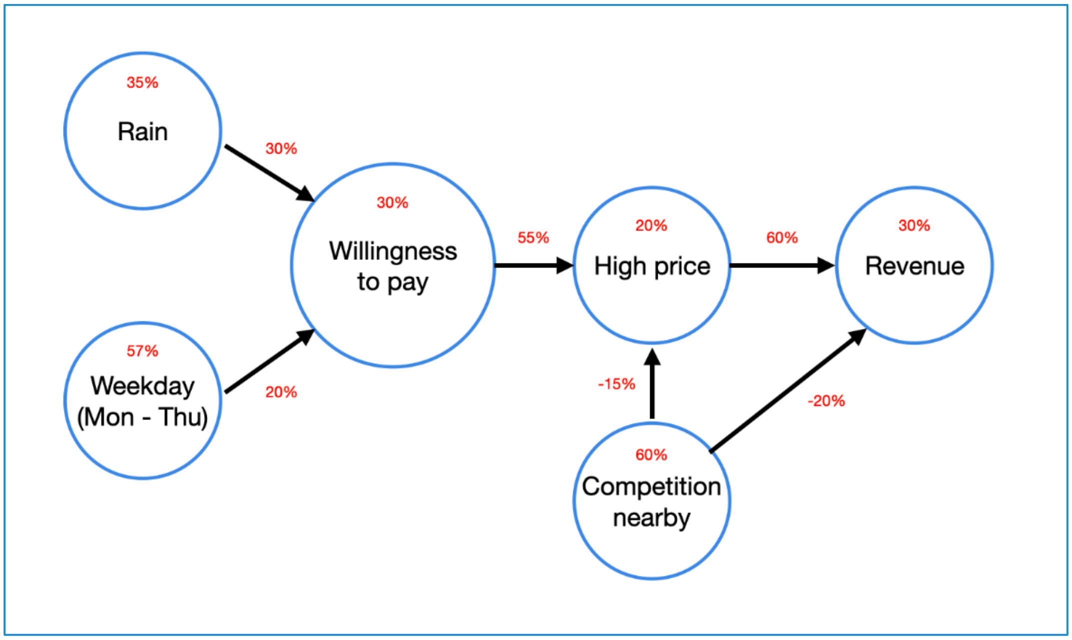


Figure 3.1

Attribute 1: Rain

The attribute indicates if there is **rain** on a given day. Based on the different estimations of the percentage of rainy days in Milan, we assign the probability of 35% to the Rain Attribute.

Attribute 2: Weekday

The attribute stands for whether it is **weekday** (Monday to Thursday) in contrast to the **weekend** (Friday to Sunday). We group Friday with Saturday and Sunday because we believe that on Fridays people are more likely to use their cars to fulfil plans not associated with routine working days' activities. We assign the probability of 57% to the attribute because we believe that the willingness to pay of a person during weekdays is significantly higher given that people commuting to work prefer to spend less time finding a parking slot.

Attribute 3: Willingness to pay

The attribute represents how much the customers are **willing to pay** in order to use the parling lot facilities. We believe that there is a 30% probability that a person will have high willingness to pay in the absence of rain during the weekend, since good weather on a weekend may influence a person to take public transport.

Our assumptions on the links from rain and day of the week to willingness to pay are backed by the **analysis of secondary** data provided by Quick No Problem Parking. Indeed, the company gave us a dataset containing the number of accesses and the revenues from the parking lot in Milan (directly below Bocconi University). This analysis helped craft our assumption in a more **data-driven** way.

We assume that rain **increases** the willingness to pay for a parking lot by 30% for two main reasons. Firstly, a driver may want to keep the car in a more secure place than the street during bad weather to protect the car from potential damage. Secondly, it is more likely that a driver will choose proximity to the destination during the storm over potential lower price at a farther parking lot to avoid walking in the rain to the final destination.

The **positive sign** of the link is backed by the **secondary data analysis** of the daily number of customers and cash inflow depending on the weather. As can be seen from Figure 3.2 during rainy days more people use the car in comparison to days with good weather.

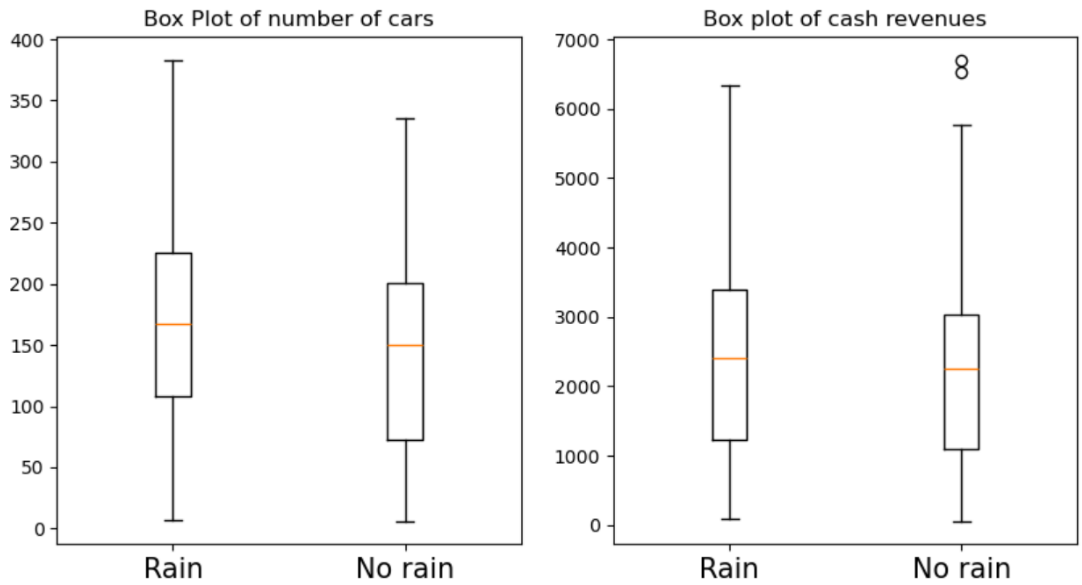


Figure 3.2

By our belief, the weekday increases the willingness to pay by 20% because people might have more concrete plans during working days.

The assumption that the link from weekday to the willingness to pay is positive is backed by the **secondary data analysis** of the daily number of customers and cash inflow. In the graph and table below, it can be seen that the demand for the parking spaces is **higher** during working days, thus pointing to the idea that the implementation of dynamic pricing could potentially **benefit revenue generation.**

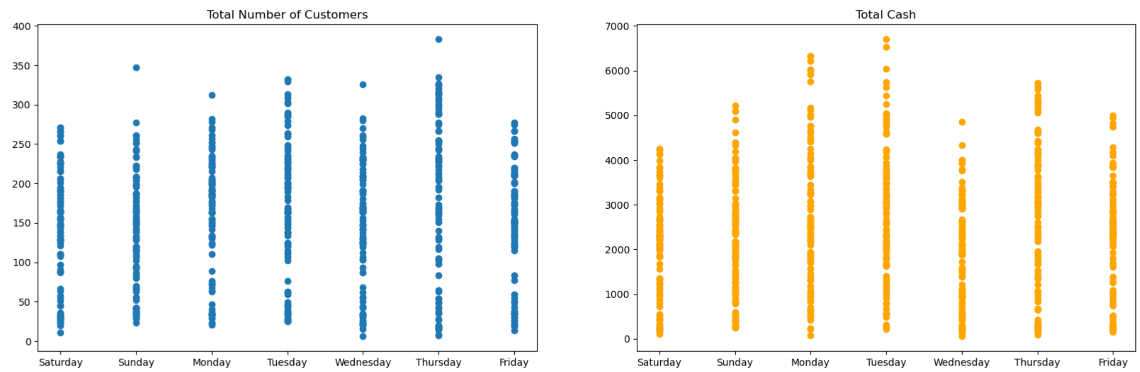


Figure 3.3

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Mean Number of Customers	162.05	170.85	146.19	180.85	151.03	142.91	137.83

*the difference is statistically significant (low p-value in the ANOVA test)

Attribute 4: High price

The attribute represents the price of using a parking lot. We believe that the probability of a high price is 20% if there is no nearby competition but people have very low willingness to pay. If a company knows that its customers are willing to pay a lot for the services, the probability of a higher price **increases** by 55% by our assumption, while the presence of **competition** nearby **drives the price down** by 15%.

Attribute 5: Competition nearby

The attribute indicates the presence of **competition** with neighbouring parking lots. We assign it the probability of 60% due to the variety of parking spaces existing in Milan.

Focal Attribute: Revenue

The final attribute of interest is the **revenue** of the company. We believe that the probability of a parking lot collecting high revenue is 30% in the absence of competition and with low prices.

Setting high **prices increases** said probability by 60% since our belief is that the demand for parking spaces is quite inelastic. **High competition** nearby would **decrease** the revenue by 20% by driving the customers away.

We are 55% confident that the theory is true because some of the links are backed by the primary data analysis while other links are based on assumptions.

The conditional expected **probability** of the theory is:

$$V(\theta) = 0.3 + ((0.35*0.3+0.57*0.2+0.3)*0.55 + 0.2 - 0.15*0.6)*0.6 - 0.2*0.6 = 0.42$$

The expected probability of the theory under the **null hypothesis** is:

$$V_{\tilde{\theta}} = 0.35$$

The **confidence level** is:

$$\omega = 0.55$$

Therefore, the **unconditional expected value** is:

$$\text{Expected value} = \omega V_{\theta} + (1-\omega)\, V_{\tilde{\theta}} = 0.55 * 0.42 + (1 - 0.55) * 0.35 = 0.39$$

b. Second theory: subscription bundle

Our second theory proposes the introduction of a new type of subscription, a **premium subscription,** which forms a bundle of services between Quick Parking and various coffee shops located in the parking area. This premium subscription would allow the holder to enjoy two soft drinks, choosing from coffee, hot chocolate, and tea, every day.

The development of this second theory, much like the first, originated from our initial insights. As we developed it further, we reinforced and consolidated it by reviewing various **articles** (Castagna, 2022) and **papers** (Derdenger & Kumar, 2012). The concept of offering bundled services is widely prevalent, and extensive literature indicates it as a highly effective tool for increasing sales and enhancing brand perception among customers. However, applying such a bundled structure to parking services in conjunction with local coffee shops is an **unusual approach**. The choice of the bundle's components is also intentional. Our goal was to create a **symbiotic relationship** between the two businesses, leveraging the high consumption of coffee and similar beverages, especially during workdays.

Supporting this idea, data from the *Centre for the Promotion of Imports* from developing countries (CBI) shows significant coffee importation levels. In 2021, Italy was the **second-largest coffee importer in Europe**, only behind Germany (Davidson, 2021). According to

2021 consumption data, an average Italian consumes **4.9 kg of coffee** annually, placing them among the world's leading coffee consumers, ranking fourteenth in 2021 (Ozbun, 2023).

This data underscores the **potential effectiveness** of our premium subscription model. By associating the daily ritual of coffee drinking with parking services, we aim to enhance the attractiveness of our parking subscription, making it not just a utility service but also a **daily lifestyle choice**. This strategy could lead to increased subscription rates, higher customer satisfaction, and stronger brand loyalty, all while supporting local coffee shops and fostering a sense of community among the users of our parking facilities.

The structure of our network can be seen on the graph below:

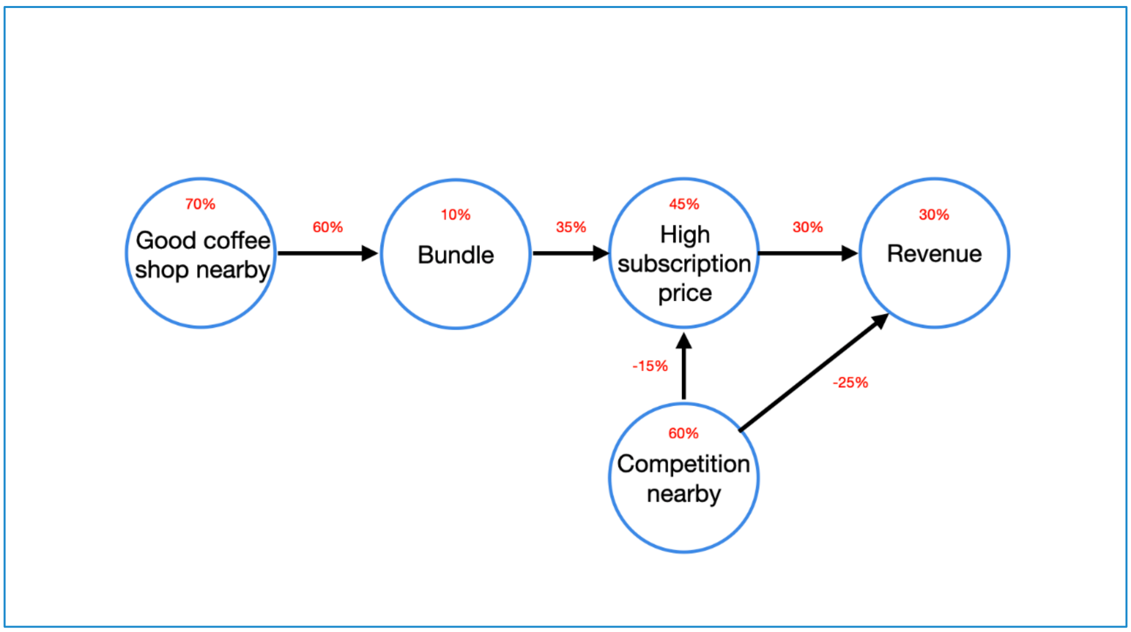


Figure 3.4

Attribute 1: Good coffee shop nearby

The attribute indicates the **presence of a good coffee** place within walking distance of the parking lot, so that it would be convenient for a driver to go to after parking their car in said parking lot. Our belief is that the probability of this attribute is 70% due to the abundance of coffee places in Italian cities.

Attribute 2: Bundle

The attribute represents the feasibility of introducing a **bundle subscription**. We assume that offering a bundle with a coffee shop is highly unlikely in the absence of good bars within reach of the parking lot, thus assigning the probability of 10% to the attribute. The presence of coffee places would, in turn, increase the probability of implementing the premium subscription by 60%.

Attribute 3: High subscription price

The attribute stands for the possibility of offering a **high price** for the parking lot subscription. The assumption here is that the probability of this attribute without a bundle is 45% in the absence of competition with neighboring parking lots, since lack of competitors lets you increase the prices but there is a limit to what a company can do with its prices in order to attract and keep customers. We believe that adding a coffee shop subscription to the offer **increases** the probability of high prices by 35%, while nearby competitors **decrease** said probability by 15%.

Attribute 4: Competition nearby

The attribute represents the **presence of competing parking lots**. We assign the probability of 60% to the attribute due to the variety of parking spaces existing in Milan.

Focal Attribute: Revenue

The main attribute of interest is the **revenue** of the company. We assume that the probability of a parking lot collecting high revenue is 30% in the absence of competitors and with low subscription prices. **High bundle subscription prices increase** said probability by 30% since our belief is that introducing a premium subscription would get a positive response from the customers. **High competition** nearby would **decrease** the revenue by 25% by driving the customers away.

The **expected probability** of the theory is:

$$V(\theta) = 0.3 + ((0.7*0.6 + 0.1)*0.35 + 0.45 - 0.15*0.6)*0.3 - 0.25*0.6 = 0.31$$

The expected probability of the theory under the **null hypothesis** is:

$$V_{\tilde{\theta}} = 0.25$$

Our **confidence level** is:

$$\omega = 0.45$$

Therefore, the **unconditional expected value** is:

$$\text{Expected value} = \omega V_{\theta} + (1-\omega)\, V_{\tilde{\theta}} = 0.45*0.31 + (1 - 0.45)*0.25 = 0.28$$

4. Survey design

The foundational principles on which this questionnaire was developed aimed at creating an experience that was as **streamlined** and **clear** as possible. Indeed, the number of questions posed to respondents was capped at nine, with each question being meticulously crafted to avoid overly long and complex queries, while maintaining their intended effectiveness.

As sketched in Figure 4.1 (the full workflow of the survey can be seen in Table 6 in the Appendix), the structure of the questionnaire features **two main branches** following the first five questions that gather demographic data.

The division of the questionnaire includes a **first branch** dedicated to the first theory, consisting of three questions presented to anyone on this track and one randomly selected from four options.

The **second branch** involves a single common question for all participants, with the response to this question leading to either a single final question or a random choice between the two.

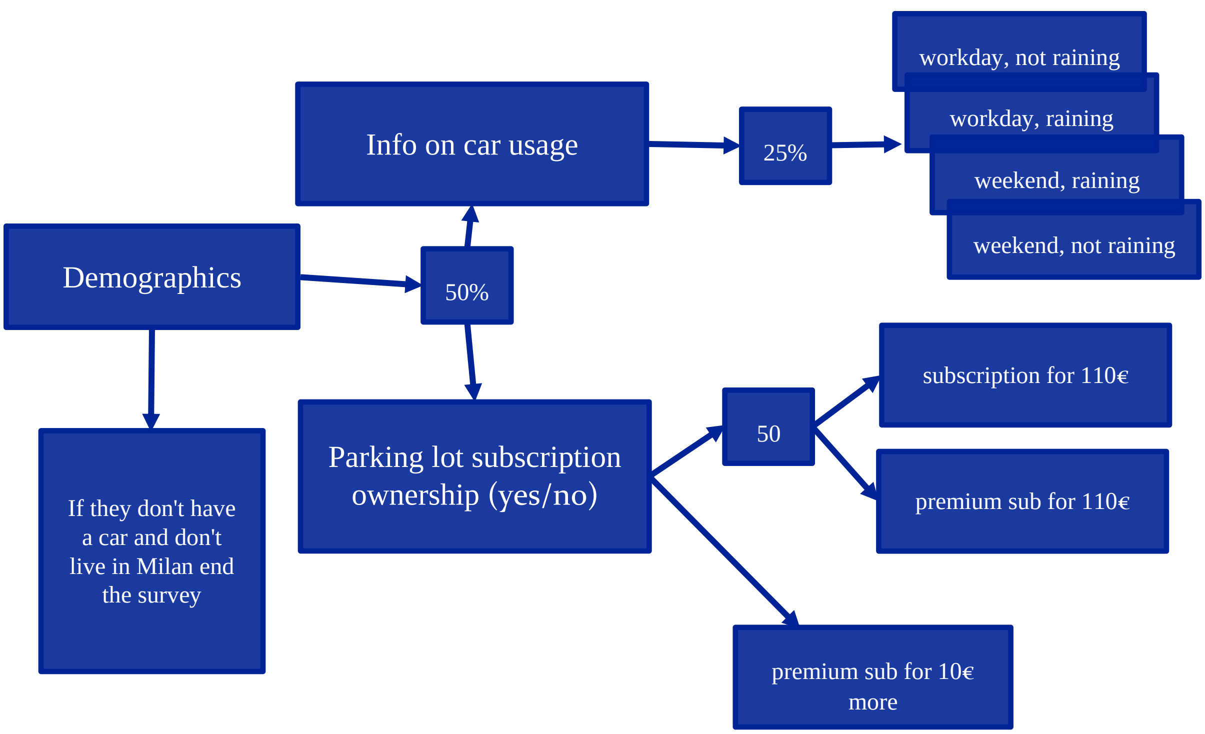


Figure 4.1

This structure of the survey was designed to tailor questions specifically to the type of theory being investigated. Undoubtedly, this fragmentation **may have impacted the volume** of data collected, but it also provided us the opportunity to ensure that the data gathered was more **significant** and **insightful**.

The primary subjects we aimed to involve through the survey were all individuals **residing in Milan**, or those who frequently visit the city, who possess a **driver's license**.

Given the scope of participants we could potentially reach, we were already aware that the individuals who would engage with our questionnaire would primarily be those residing or frequently visiting the Milan metropolitan area. For this reason, we made a conscious decision to target only those who were, without a doubt, residents or regular visitors of Milan.

While this decision was logical, it raises an important issue: considering the extensive coverage that Quick No Problem Parking offers across the entire Italian territory, the ideal approach would have been to develop a **specific questionnaire for each city** where they operate, with pricing and questions tailored to the local context.

In fact, it is not guaranteed that the habits and customs of the Milanese population will align with those of other cities. This means that while our results are undoubtedly significant for Milan, we cannot ascertain their validity for other cities. This situation potentially risks **compromising the external validity** of our findings.

Developing city-specific surveys would have enabled us to capture **diverse local perspectives** and needs, providing a more comprehensive understanding of the different contexts in which the company operates.

Demographic questions

The first section of the questionnaire was designed to gather **general information** through 5 questions. The first 3 aimed to identify age, gender, and occupation. The last 2 asked whether the respondent had a driving license and if they frequently visited or lived in Milan; if either of these two answers was negative, the survey would **conclude**. This was because those individuals would not be potential customers for the parking lot in Milan.

Track 1: prices

In the section of the survey dedicated to testing the first theory, participants were presented with a series of questions, each aimed at exploring different aspects of their **transportation habits** and preferences. Initially, everyone assigned to this track encountered three standard questions.

The first of these sought to identify the days of the week when respondents most frequently used their cars, providing insights into **weekly patterns**.

Following this, a question asked about the participants' preferences among various types of parking facilities under different weather conditions, such as preferring covered parking during rain.

The third question was designed to understand the balance individuals strike between the cost of parking and its proximity to their destination, a crucial factor in urban mobility choices. This question was particularly significant in assessing how **price sensitivity** and **convenience influenced parking decisions**.

Subsequent to these initial questions, the survey introduced an element of **randomness**: participants were presented with a randomly selected question from a set of **four**. This method aimed to create four randomized groups which we could use to perform causal inference. Each of these four questions depicted a **specific scenario**, either a typical weekday or a weekend day, coupled with varying weather conditions - rain or clear skies.

The intent was to simulate real-life situations and observe how these different contexts might affect individuals' choices regarding car usage and parking.

Track 2: subscription

The second section of the survey, focused on testing the **second theory**, started with a question asking whether the participant had a parking subscription. A positive response directed the participant to a follow-up question, offering the opportunity to upgrade to a **premium subscription** for an additional €10. This premium subscription included the benefit of **two daily soft drinks** (coffee, tea, or hot chocolate) at a nearby café. The purpose of this question was to understand the potential conversion rate from standard to premium subscriptions if such a policy were introduced.

Conversely, for those who answered negatively to having a parking subscription, a **randomized question** from two options was presented. One option offered the chance to subscribe to a **standard parking service** for €110, while the other proposed a **premium subscription** at the same price, inclusive of the aforementioned benefits. The rationale behind this structure was to test whether non-subscribers would perceive any difference in value between paying €110 for a standard subscription or the same amount for a premium one, thereby assessing the **attractiveness of additional perks** in influencing subscription choices.

5. Statistical analysis

a. Preparing the data

Before starting with our analysis, we had to do some **data cleaning**. More specifically, after dropping columns useless for our analysis (e.g., time and date of submission) the next step was to drop the responses for:

- Individuals without a driving license as there are not in our population of interest
- Individuals not living in Milan since those would be not in our population of interests
- The single individual reporting an age lower than 18 because people this young cannot drive a car in Italy.

After doing this we were ready to proceed.

a. Descriptive Questions

The first step is to look at the first questions of our survey which we can refer to as "**descriptive questions**". The aim of these questions was to probe the preferences of the company's potential customers.

The first 3 questions were answered with a **likert scale** from 1 to 5, to see the preferences we can look at the mean and the median answer to get a sense of the preferences.

We have that:

- for the first question "I take the car more when it rains" the mean is ~3.42 and the median is 4.
- for the second question "I generally like covered parking lots" the mean is ~2.74 and the median is 3.
- for the third question "I prefer covered parking lots when it rains" the mean is~3.41 and the median is 4

These results **confirm** our theory (and indeed is not very surprising) as we see that people are more likely to take the car when it rains. Moreover, it is worth noting that, using question 2 and 3, we see that there is a difference in the preferences of people for covered parking spaces depending on weather conditions. This means that Quick No Problem Parking's covered parking lot in Milan has higher potential demand when it rains.

We have then a **semantic scale** asking respondents if their choice of parking lot is motivated more by price or by proximity to their destination and the result is that **price is the driving**

factor. We have to take this into account since our theory is that demand, under certain conditions, is quite inelastic.

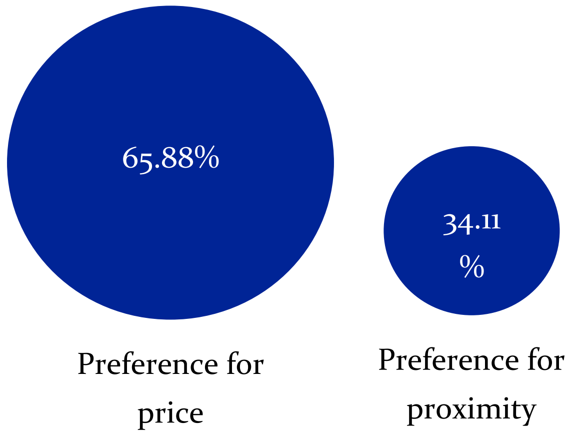


Figure 5.1

The last question is instead related to the link "**weekend vs weekday**". In this sense we see that close to 50% of respondents use their car from Monday to Thursday while close to 70% use their car from Friday to Sunday.

This result seems to partially contradict our theory and perhaps can be explained by the fact that people living in Milan take their car mostly to go away on weekends rather than to go to work/university.

b. Testing the first theory

Randomization checks

Since we want to perform a regression and interpret as causal the results we found, we need data from 4 **correctly randomized** groups. Qualtrics should have taken care of this but a further check we can do is to look at the covariates age, gender and occupation, which could potentially affect the result of the analysis, to see if there is a difference between the groups.

To do this we tabulate the frequencies of possible choices for age, gender, occupation and perform a chi-square test to see if the distribution of the 4 treatment groups is identical.

For all three covariates the counts look very similar among the groups and indeed, performing a Pearson chi-square test we **fail to reject** the null (p-values shown in Table 5.1, full tabulations are in Table 1 in the appendix) that the distribution is different.

stat	gender	age	occupation
Chi-sq statistic	3.059	10.011	5.452
p_value	0.801	0.35	0.487

Table 5.1

Regression

We can move then to regression. The model we estimate is a **linear regression** with the willingness to pay, specified by respondents, as the dependent variable. Regressors are the first treatment (rain), the second treatment (weekday), an interaction term between the treatments and all controls (age, gender, occupation). The OLS estimates were computed with robust standard errors.

The model (without controls to make it more readable) would be:

$$y_i = b_0 + b_1 rain + b_2 weekday + b_3 rain * weekday$$

The result (full table shown in Table 2 in the appendix) is that: coefficients on weekday and on the interaction term between the two treatments are not significant, while the coefficient on **rain** is **positive** (~0.68) and **significant** at the 5% level.

	coef	std err	z	P>|z|	[0.025	0.975]
treatment_rain	0.6857	0.336	2.039	0.041	0.026	1.345
treatment_weekday	-0.0900	0.369	-0.244	0.807	-0.814	0.634
interaction_term	0.3539	0.527	0.671	0.502	-0.680	1.388

Table 5.2

Interpretation of results

The only significant coefficient is on treatment_rain (b1) this means that the willingness to pay is higher **only when it rains**. Indeed, coefficient b1 captures the increase of y when rain=1 and weekday=0. If there was an effect of the day of the week on the willingness to pay, we would expect also b2 (effect when rain=0 and weekday=1) and b3 (both rain=1 and weekday=1) to be significant.

From the table it is immediate to see that people are on average willing to pay ~0.70€ more for a parking spot when it is raining.

Since we have four randomized groups, assuming:

- **full compliance**: respondents looking at the question have automatically "taken the treatment",
- **excludability**: we can assume there are no confounding factors in our analysis that obscure the actual effect of the treatment,
- **SUTVA**: we can reasonably assume that people were not influenced in their answers by other respondents,

this coefficient can be interpreted as the **ATE** of having a rainy day on the willingness to pay for a covered parking lot.

Looking at these results we **increase** the probability for the link between *rain* and *willingness to pay* and **decrease** the probability for the link between *weekday* and *willingness to pay*

d. Testing the second theory

Randomization checks

Same as for the first theory, we want to have a control and a treatment group that are **correctly randomized**. The distribution of the three covariates looks for the control and treatment group look very similar and indeed performing a Pearson chi-square test we **fail to reject** the null (*p-values* shown in the table, full tabulations are in table 3 in the appendix) that the distribution is different.

stat	gender	age	occupation
Chi-sq statistic	0.186	4.121	0.728
p_value	0.666	0.249	0.695

Table 5.3

Regression

In this case we have a binary outcome (yes/no) therefore we need to use a **logistic regression.** The dependent variable is the answer to the question *"would you buy the subscription"*.

Regressors are the treatment (individual is treated if they were offered the bundle) and controls for age, gender and occupation.

The model (without controls to make it more readable) is:

$$y_i = b_0 + b_1 treatment + b_2 male + b_3\ dummyage1 + \cdots`$$

The result (full table shown in Table 4 in the appendix) is that the coefficient on treatment is positive but **not significant**.

	coef	std err	z	P>|z|	[0.025	0.975]
treatment	0.6756	0.539	1.252	0.210	-0.382	1.733
intercept	-3.6370	1.348	-2.699	0.007	-6.278	-0.996

Table 5.4

Interpretation of results

Given that the treatment was assigned randomly to half of the respondents, assuming **full compliance**, **excludability** and **SUTVA**, we can interpret the coefficient on treatment as the **ATE**. Therefore, we can conclude that that the offer of a bundle **does not increase** the number of people buying the subscription.

Looking at this result, we would **decrease** the probability of the link between *bundle* and *high subscription price* in our theory.

e. Limitations

The analysis we made has, as predicted, some limitations which may decrease the 'internal validity' of our study, that is our ability to correctly identify the *ATE*.

In this example possible threats to internal validity are:

- violations of the **excludability** conditions. There may be indeed some other factors that we have not considered that actually drives the effect that we have seen and interpreted as ATE
- violations of the **SUTVA** assumption. Responses may have been influenced by seeing one of the other possible questions ('treatments') before answering.
- **Hawthorne effect**. Respondents in the treated group, knowing or imagining the goal of the survey, may have felt the need to give answers that confirmed our theory. This

may be especially problematic since a significant part of our responders were either our classmates (who knew exactly the scope of this project), or in general people who knew us for whom it would not be too difficult to figure out the expected outcome of the survey looking at the questions.

Another important limitation is the limited **sample size**. We managed to reach over 200 people however, after dropping all those who did not have a license lived far from Milan and splitting them in all the different groups, we were left with a small sample size (approx. 20 individual per group for the theory about price and approx. 80 per group for the bundle theory).

Having a small sample size is problematic because results of our regressions with robust standard errors are only "**consistent**". This means that we can correctly identify the ATE only in the limit of n going to infinity (that is with "large" samples).

7. Updating the theory

After observing the results of the experiments, we need to update the probability associated to the links of our theory as well as the confidence level

Dynamic pricing

The results of the regression as well as the descriptive questions tell us that people are indeed **more likely** to take the car when it rains and are **willing to pay more**. We can therefore **increase** the probability of the link between *rain* and *willingness to pay* in our Bayesian network from 30% to 60%.

On the opposite side we have observed that the *day of the week* does not have any effect on the willingness to pay so we can **decrease** the probability of that link from 20% to 10%

Since we have observed that, under some conditions, demand for covered parking spaces is inelastic, we also **update our confidence** level from 55% to 85%

We can then compute the **unconditional expected value** of our updated theory as

$$V(\theta) = 0.3 + ((0.35*0.6+0.57*0.1+0.3)*0.55 + 0.2 - 0.15*0.6)*0.6 - 0.2*0.6 = 0.44$$

$$V_{\tilde{\theta}} = 0.35, \quad \omega = 0.85$$

$$\text{Expected value} = \omega V_\theta + (1-\omega)\, V_{\tilde{\theta}} = 0.85 * 0.44 + (1 - 0.85) * 0.35 = 0.43$$

Subscription bundling

The results of the regression suggest that having a bundle with a subscription to a coffee shop **does not increase** the likelihood that people buying a subscription. We have then to decrease the weight of the link between *bundle* and *high subscription price* of our network from 35% to 15%

Since we have observed that the main assumption of our theory is not reflected in the data, we also **update the confidence level** from 45% to 25%.

We can then compute the **unconditional expected value** of the theory as:

$$V(\theta) = 0.3 + ((0.7*0.6 + 0.1)*0.15 + 0.45 - 0.15*0.6)*0.3 - 0.25*0.6 = 0.28$$

$$V_{\tilde{\theta}} = 0.25, \quad \omega = 0.25$$

$$\text{Expected value} = \omega V_\theta + (1-\omega)\, V_{\tilde{\theta}} = 0.25*0.28 + (1 - 0.25)*0.25 = 0.25$$

8. Conclusions and recommendations

In the process of analyzing QuickParking's potential customer preferences and behaviors, we gathered a lot of information and revised out initial theories.

First the **descriptive questions** revealed important insights, highlighting a preference for covered parking during rainy conditions and a price-driven choice for parking over proximity. In addition, the usage of cars during weekdays versus weekends challenged our initial assumptions, indicating a preference for car usage during the weekends.

The **collection and analysis of primary data** using surveys revealed that a statistically significant increase in willingness to pay for covered parking during rainy days. On the contrary, opposite to our expectations, the day of the week showed no significant effect. As for the bundled subscription offer, the analysis revealed **no significant increase** in subscription likelihood among respondents who were offered the bundle compared to those who weren't.

Therefore, given the **positive impact** of rainy weather on willingness to pay for covered parking, our recommendation for Quick No Problem Parking is to consider investing in the creation of a mechanism to increase prices on rainy days, to capitalize on this weather-driven demand (0.43 for the first and 0.25 for the second).

Despite the two are not being completely alternative investments, we recommend the company's management to focus efforts on leveraging and optimizing strategies related to **weather-driven pricing** as it has the highest expected value among the two.

Looking at the coefficient in our regression, a possible suggestion for implementation is to raise the price by 0.50€ on days when the weather forecast says it will rain. We believe that this price increase should be a whole number and should be made at the beginning of the day to minimize uncertainty about prices, which could "scare" away potential clients.

In the end we want to note that to note that our analysis, while informative, has some **limitations** (discussed above) which could affect the reliability of our interpretations and recommendations.

For instance, our choice of bundle is only **one among many possibilities** the company could experiment with. In the same fashion the price of the bundled subscription was set at 110€ but this choice is not the only possible option. It may be that offering a lower price the company can acquire a significant number of new customers, creating a stable revenues stream.

Our suggestion is then to refine the analysis through **further investigations** with more extensive data collection, or assessing if our findings hold in other locations in which QuickParking operates.

Bibliography

Castagna, G. (2022, April 17). *Bundle per la vendita al dettaglio: come raggruppare i prodotti per aumentare le vendite*. Retrieved from shopify.com: https://www.shopify.com/it/blog/bundle#:~:text=Anche%20se%20pu%C3%B2%20essere%20una,acquistare%20pi%C3%B9%20e%20pi%C3%B9%20volte

Centre for the Promotion of Imports from developing countries (CBI). (2022, December 23). *What is the demand for coffee on the European market?* Retrieved from https://www.cbi.eu/market-information/coffee/what-demand

Davidson, B. (2021, June 20). *The World Coffee Index 2021: The Cost and Consumption of Coffee Around the World*. Retrieved from cashnetusa.com: https://www.cashnetusa.com/blog/world-coffee-index-2021-cost-and-consumption-coffee-around-world/

Derdenger, T., & Kumar, V. (2012, February 22). *The Dynamic Effects of Bundling as a Product Strategy*. Retrieved from Harvard Business School Working Knowledge: https://hbswk.hbs.edu/item/the-dynamic-effects-of-bundling-as-a-product-strategy

OpenAi. (2023). *ChatGPT*, November 2023. Retrieved from https://chat.openai.com/

Ozbun, T. (2023, January 31). *Coffee market in Italy- Statistics & Facts*. Retrieved from statista.com: https://www.statista.com/topics/4053/coffee-market-in-italy/#topicOverview

Professione Accoglienza. (2023, May 5). Retrieved from La tariffazione dinamica: https://www.professioneaccoglienza.com/la-tariffazione-dinamica/

Quick No Problem Parking S.p.a. (n.d.). Retrieved from https://quickparking.it/gruppo-quick/

Tridens technology. (2023, May 18). *Che cos'è il Dynamic Pricing e come utilizzare la strategia di Dynamic Pricing?* Retrieved from https://tridenstechnology.com/it/prezzo-dinamico/

Appendix

Table 1: first theory – contingency tables for gender age and occupation

Contingency Table:

treatment	Female	Male	Non-binary	Total
dry_weekday	8	11	1	20
dry_weekend	12	10	0	22
rainy_weekday	9	9	1	19
rainy_weekend	12	11	0	23
Total	41	41	2	84

Chi-squared test:
Chi-squared statistic: 3.0586
Degrees of freedom: 6
P-value: 0.8015

Contingency Table:

treatment	18-23	24-35	36-55	>55	Total
dry_weekday	12	2	3	3	20
dry_weekend	18	0	3	1	22
rainy_weekday	14	2	3	0	19
rainy_weekend	19	2	2	0	23
Total	63	6	11	4	84

Chi-squared test:
Chi-squared statistic: 10.0106
Degrees of freedom: 9
P-value: 0.3496

Contingency Table:

treatment	Student	Working	other	Total
dry_weekday	12	6	2	20
dry_weekend	16	5	1	22
rainy_weekday	14	5	0	19
rainy_weekend	15	4	4	23
Total	57	20	7	84

Chi-squared test:
Chi-squared statistic: 5.4516
Degrees of freedom: 6
P-value: 0.4873

Table 2: ols(outcome ~ gender + occupation + age + treatment_rain + treatment_weekday + interaction_term)

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                outcome   R-squared:                       0.199
Model:                            OLS   Adj. R-squared:                  0.090
Method:                 Least Squares   F-statistic:                     2.382
Date:                Thu, 23 Nov 2023   Prob (F-statistic):             0.0167
Time:                        12:16:55   Log-Likelihood:                -120.51
No. Observations:                  84   AIC:                             263.0
Df Residuals:                      73   BIC:                             289.8
Df Model:                          10
Covariance Type:                  HC3
=========================================================================================
                            coef    std err          z      P>|z|      [0.025      0.975]
-----------------------------------------------------------------------------------------
Intercept                 1.3109      0.247      5.300      0.000       0.826       1.796
gender[T.Male]            0.4632      0.255      1.814      0.070      -0.037       0.964
gender[T.Non-binary]      0.0343      0.444      0.077      0.938      -0.836       0.905
occupation[T.Working]     0.1888      0.682      0.277      0.782      -1.147       1.525
occupation[T.other]      -0.2282      0.377     -0.605      0.545      -0.968       0.511
age[T.24-35]              0.4916      0.582      0.844      0.398      -0.649       1.633
age[T.36-55]              0.0237      0.813      0.029      0.977      -1.569       1.616
age[T.>55]                0.5703      1.412      0.404      0.686      -2.196       3.337
treatment_rain            0.6857      0.336      2.039      0.041       0.026       1.345
treatment_weekday        -0.0900      0.369     -0.244      0.807      -0.814       0.634
interaction_term          0.3539      0.527      0.671      0.502      -0.680       1.388
==============================================================================
Omnibus:                        4.434   Durbin-Watson:                   2.219
Prob(Omnibus):                  0.109   Jarque-Bera (JB):                4.319
Skew:                           0.287   Prob(JB):                        0.115
Kurtosis:                       3.951   Cond. No.                         14.2
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC3)
```

Table 3: second theory - contingency tables for gender, age and occupation

Contingency Table:

treatment	Female	Male	Total
0	20	23	43
1	23	20	43
Total	43	43	86

Chi-squared test:
Chi-squared statistic: 0.1860
Degrees of freedom: 1
P-value: 0.6662

Contingency Table:

treatment	18-23	24-35	36-55	>55	Total
0	29	2	9	3	43
1	29	7	5	2	43
Total	58	9	14	5	86

Chi-squared test:
Chi-squared statistic: 4.1206
Degrees of freedom: 3
P-value: 0.2487

Contingency Table:

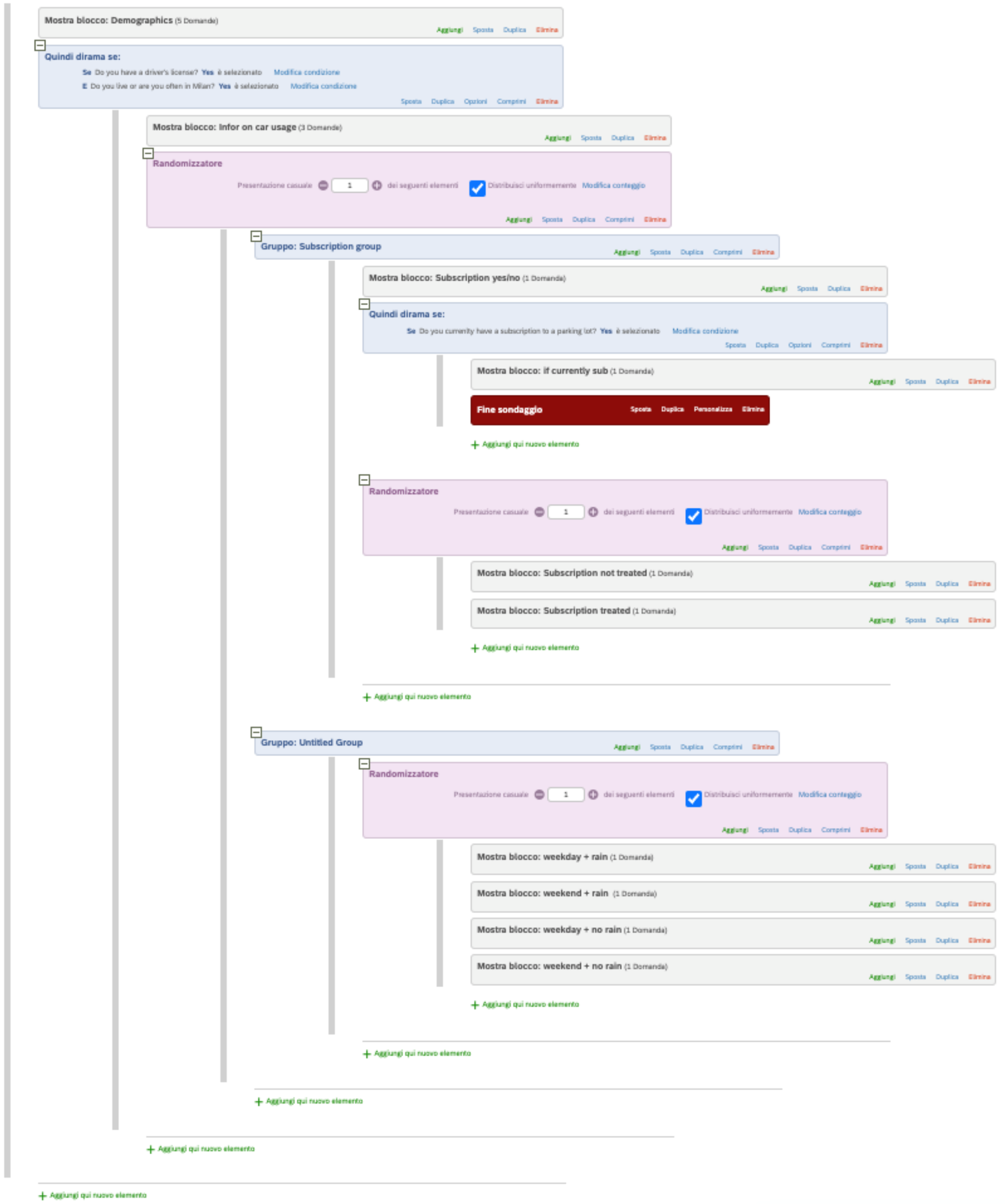
treatment	Student	Working	other	Total
0	29	12	2	43
1	28	11	4	43
Total	57	23	6	86

Chi-squared test:
Chi-squared statistic: 0.7277
Degrees of freedom: 2
P-value: 0.6950

Table 4: logit(outcome ~ gender + occupation + age + treatment + intercept)

```
Optimization terminated successfully.
         Current function value: 0.515872
         Iterations 6
                           Logit Regression Results
==============================================================================
Dep. Variable:                outcome   No. Observations:                   86
Model:                          Logit   Df Residuals:                       78
Method:                           MLE   Df Model:                            7
Date:                Thu, 23 Nov 2023   Pseudo R-squ.:                 0.04882
Time:                        12:16:55   Log-Likelihood:                -44.365
converged:                       True   LL-Null:                       -46.642
Covariance Type:                  HC3   LLR p-value:                    0.7142
=================================================================================
                    coef    std err          z      P>|z|      [0.025      0.975]
---------------------------------------------------------------------------------
treatment         0.6756      0.539      1.252      0.210      -0.382       1.733
intercept        -3.6370      1.348     -2.699      0.007      -6.278      -0.996
gender_bin        0.1872      0.545      0.343      0.731      -0.881       1.256
student_dummy     1.8854      1.267      1.488      0.137      -0.598       4.369
working_dummy     0.3394      1.278      0.266      0.791      -2.165       2.844
24-35_dummy       1.3093      1.152      1.137      0.256      -0.948       3.567
36-55_dummy       1.9133      0.989      1.935      0.053      -0.024       3.851
>55_dummy         2.5588      1.399      1.830      0.067      -0.182       5.300
=================================================================================
```

Table 5


Mostra blocco: Demographics (5 Domande)
Quindi dirama se:
Se Do you have a driver's license? Yes è selezionato
E Do you live or are you often in Milan? Yes è selezionato
Mostra blocco: Infor on car usage (3 Domande)
Randomizzatore
Presentazione casuale 1 dei seguenti elementi
Distribuisci uniformemente
Modifica conteggio
Gruppo: Subscription group
Mostra blocco: Subscription yes/no (1 Domanda)
Quindi dirama se:
Se Do you currently have a subscription to a parking lot? Yes è selezionato
Mostra blocco: if currently sub (1 Domanda)
Fine sondaggio
Aggiungi qui nuovo elemento
Randomizzatore
Mostra blocco: Subscription not treated (1 Domanda)
Mostra blocco: Subscription treated (1 Domanda)
Gruppo: Untitled Group
Randomizzatore
Mostra blocco: weekday + rain (1 Domanda)
Mostra blocco: weekend + rain (1 Domanda)
Mostra blocco: weekday + no rain (1 Domanda)
Mostra blocco: weekend + no rain (1 Domanda)
Aggiungi qui nuovo elemento