Tel Aviv University
The Gershon H. Gordon Faculty of Social Sciences
The Eitan Berglas School of Economics

The impact of positive incentives on public transportation usage: A field experiment in Israel

This paper was submitted as the thesis for the M.A. degree by:

Hadar Fuks Roich

This paper was carried out under the supervision of:
Prof. Itai Ater and Dr. Adi Shani Rotem

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Abstract

This study reports the results of an experiment examining how monetary incentives affect the use of public transit. In the study, 1455 Israeli participants were assigned to six treatment groups, which differ based on the magnitude of the monetary incentive, and participants in a non-incentivized control group. Using rider-level data on public transit usage before, during, and after the experiment, we found that on average, treated participants increased by 21.8% their usage of public transportation compared to participants in the control group. However, we did not observe the long-lasting impact on the use of public transit after the experiment ended, though this result might be driven by worsening COVID-19 conditions during the experiment and after it ended. In addition to the increase in public transportation usage, an additional analysis shows that participants that increased their public transit usage reduced their use of private vehicles during the experiment by 5.3% compared to participants who did not change their patterns. Moreover, further heterogeneity analyses show that males increased their public transit usage considerably more than females.

Contents

1 Introduction

One of the most troubling problems in the life of the average urban citizen is road congestion. Road congestion has far-reaching economic consequences - affecting workers' productivity, reducing labor supply, and harming private and leisure consumption. The INRIX Global Traffic (2021) report recently estimated the congestion cost of the UK economy by £5.9 billion in 2019. In the United States, Americans lost an average of 97 hours a year due to congestion, costing them nearly $87 billion in 2018, an average of $1,348 per driver. Ensuring public transport's effective and efficient provision is a priority for many governments and a key to providing better accessibility in urban areas (Cats et al., 2014).

The phenomenon exists even more strongly in Israel. For example, the OECD (2019) report estimates the congestion costs in Israel at around 2% of GDP, above other high-income economies such as western Europe and the USA. Effective solutions for this problem are establishing mass transit systems like the Light Rail and the Metro projects and improving the quality of public transportation (Ministry of Transport and Road Safety, 2007). However, such solutions take time and cannot solve the problem in the short-term. According to The The State Comptroller (2019) report to see relief in the short-term, it is necessary to implement a policy that reduces the demand for private car and increases the demand for public transportation.

This study uses a field experiment in Israel to examine how monetary incentives affect public transportation usage. In the three-weeks experiment, 1191 riders were randomly assigned to six treatment groups, where riders in each group received different incentives to increase their public transit usage during three weeks. We further use public transit information for 255 control group riders who did not get any monetary incentives to change their public transit usage over the same period. Importantly, the rider level data we have for riders in the treatment and the control groups extends before, during, and after the three-weeks experiment. In addition, for riders in the treatment groups, we also have rider-level data on riders' usage of their private vehicles. These data allow us to examine substitution patterns between the use of private vehicles and public transit. We have three main goals in conducting the experiment. First, to investigate the sensitivity of riders' public transit usage to monetary incentives. Although public transit prices likely have an important role in shaping riders' use, a large body of evidences shows that factors such as reliability and convenience are primary determinants of public transit usage (Litman, 2008). Second, to explore whether short-term increases in public transit usage have a long-lasting impact on public-transit use. Naturally, if short-term incentives can affect riders' long-lasting habits, the return to policies encouraging public transit usage in the short run is considerably higher than otherwise. Finally, we want to measure the substitution between public transit usage and private vehicles. Importantly, policymakers are interested in quantifying to what extent subsidizing public transit contributes to the lower usage of private vehicles as a means to reduce congestion and pollution. However, since most studies use aggregate-level data, it is inherently difficult to identify the substitution between different transportation modes. Our project, therefore, provides a unique opportunity to examine these substitution patterns.

In late 2019, a large-scale government experiment called "Derekh Erekh" was launched. In this experiment, 15,000 riders were given incentives to reduce the usage of their private cars in an attempt to reduce congestion and learn about riders' use of private vehicles. The public-transit experiment, which is the center of the current paper, is a spin-off of the large experiment. At the time of recruitment for the "Derekh Erekh" experiment, riders signed a consent form that allowed the research team to monitor and access not only private car usage data but also data on their usage of public transit. The public transit data is available only for riders with a personalized public transit id card. These drivers are the sample used for the public transit experiment, which is the center of the current study. Participants were divided into treatment and control based on the date of joining "Derekh Erekh." Participants in the treatment group were randomly assigned to six treatment groups based on a block mechanism design. The difference between the treatment groups was the value of the daily incentive that participants received in exchange for using public transportation. At the end of the experiment, participants received the accumulated amount they earned in the form of a gift card, up to a ceiling of NIS 150.

In the empirical analysis, we use the difference-in-semielasticities (DIS) estimation method (Shang et al., 2017) which captures the difference between the average public transit usage change rate among the treatment group and the average change rate among the control group. Our estimation results show that riders in all treatment groups significantly increased their public transit usage. The effect we quantify ranges between 15.7% and 33.1%, where the average impact across all treatment groups is 21.8%.

However, no monotony effect was detected across groups. That is, we do not find that riders that faced stronger monetary incentives increased their public transit usage more than riders who faced weaker incentives. Moreover, shortly after the experiment ended, the public transit usage by riders in the treatment group returned to its pre-experiment level, or more precisely, to the usage level of riders in the control group. We discuss the possible explanations for our findings below and highlight complications that likely have occurred due to an abrupt rise in COVID-19 cases during the three-weeks experiment and the following weeks (see Figure 4 in the Appendix).

A central part of the research examines the substitution between public transportation and private vehicles. The participants in the treatment groups were classified into two groups based on their changing patterns compared to the control group. By our estimations, participants who increased their usage of public transit reduced their use of private vehicles by 5.3% compared to participants who did not change their public transit habits during the experiment.

Moreover, heterogeneity analysis was performed. Heterogeneity analysis allows concluding participants' willingness to change their behavior according to socioeconomic and demographic characteristics. This analysis is essential as it can help policymakers determine how to allocate resources to improve public transportation and establish appropriate infrastructure by effective priorities. The analysis was done by adding an additional interaction dimension to the estimation equation and examining the DIS differences. Of all characteristics we examined, the difference between males and females is the most significant. In all treatment groups, males increased the amount of their trips by public transportation compared to females.

The remainder of the paper is organized as follows: Section 2 provides a literature review concerning the effects of fares on public transport demand and results from previous experiments. Section 3 describes the experimental methodology, including the data structure, incentives, and allocation mechanisms. Section 4 focuses on the empirical strategy. The experiment results are presented in Section 5, and section 6 describes conclusions and further discussion.

2 Literature Review

There is extensive literature dealing with factors influencing the demand for public transportation. Litman (2008) divided those factors into several categories - demographic characteristics, commercial activity, alternatives to public transportation, land uses, demand management, and price effects. Each of these categories includes several attributes that, in one way or another, affect the demand for public transportation. For example, the "prices" category includes parking, fuel, congestion charges, public transportation fares, and more. Many studies have attempted to evaluate the elasticity of public transportation relative to different factors using different estimation methods (Goodwin, 1992; Goodwin et al., 2004; Paulley et al., 2006).

Most studies distinguish between the elasticity of public transport in the short-term compared to the long-term, assuming it takes time to change travel habits. Tsai and Mulley (2014) estimated the elasticity of demand for public transportation in the short and long term about various characteristics. They estimated the elasticity in relation to fares at about -0.21 and -0.29 in the short and long term, respectively. Their short-term results are consistent with Hensher (1998), who used a revealed preference method for estimating the elasticity.

In contrast, Dargay and Hanly (2002) and Balcombe et al. (2004) reached different results while distinguishing between urban and non-urban areas as well as between different types of transportation. Balcombe et al. (2004) estimated the short-term elasticity in relation to fares at about -0.42 in the short-term. The various range of the estimation results are due to several factors

- estimation the demand in different countries, using various estimation methods, and using other databases and explanatory variables. In addition to fares, one of the most influential factors in the use of public transport is its quality. The quality of public transportation is reflected in a number of characteristics - frequency, hours of operation, convenience, travel times in relation to alternatives, reliability, and more. Holmgren (2007) estimated the elasticity of short-term demand relative to the public transportation quality index at about 1.05.

In the past, many studies examined the effect of incentives on the behavior and habits of individuals. Thøgersen and Møller (2008) examined how granting a free pass for a month affected people's travel habits compared to a control group. They found that in the immediate term, the incentives positively affected the amount of public transport travel. However, this effect diminished over time after the trial ended. Compared to this research, a disadvantage of their study is the data quality. They collected travels data from subjective questionnaires while this study is based on reliable data from the Postal Bank. Kholodov et al. (2020) examined the impact of changing the fares policy in Stockholm in 2017. The research team found that user sensitivity grows along with the journey distance. Similarly, Cats et al. (2014) examined the influence of the Free-fare public transport policy (FFTP) in the city of Tallinn, Estonia. The study examined the impact of FFPT policy on service quality and passenger demand. One of the benefits of the their article is the ability to control changes in public transport supply and thus isolate the impact of FFTP policy. The researchers found that the policy directly impacted passengers' demand for public transport, which was reflected in a 1.2% increase in travel.

The advantage of the current study is the rider-level data. Since most studies use aggregate-level data, it is inherently difficult to identify the substitution between different transportation modes and perform a heterogeneity analysis. Our project, therefore, provides a unique opportunity to examine these substitution and heterogeneity patterns. In many studies, there is a trade-off between the available data types. Some research groups use aggregate data derived from smart cards. The advantage of this method is the wide range of data and its reliability. The disadvantage is that, in most cases, there is no way to match the travel data to the characteristics of the passengers. Only social and socio-economic characteristics can be used (e.g., unemployment rate, average income, average age). In those kinds of studies, it is not possible to identify the substitution between different transportation modes and perform heterogeneity analysis to examine how the demand for public transportation varies depending on relevant factors such as gender, age, area of residence, marital status, and more. Another type of research is based on analyzing travel patterns in public transit by answering questionnaires. This approach's advantage is that socio-economic characteristics exist at the rider-level and are necessary to perform heterogeneity analyses. The downside is that all the information about public transit usage comes through answering questionnaires. Therefore, the research is subject to the respondents' subjectivity and can be biased. The most significant advantage of the current study is the combination of the two approaches. On the one hand, data on travel by public transport comes from the Postal Bank, which is frequently, reliable, and is not affected by the respondent's opinion. On the other hand, each experiment participant must have identifiable details. The combination of the two allows for examining the impact of monetary incentives on public transport travel habits alongside in-depth heterogeneity analyses and substitution to a private vehicle.

3 Method

This study is a spin-off of the national experiment "Derekh Erekh." "Derekh Erekh" was designed to examine the willingness of participants to change their travel habits in a private vehicle due to the imposition of congestion charge. The experiment encourages participants to avoid paying the congestion charge by changing travel times, using public transportation, working from home, or carpooling. The study is still ongoing; to date, around 15000 participants have been recruited from around the country. One condition of participation is that each participant must owns a car. After joining "Drech Erech," participants' travels are monitored. Public travels are monitored by tracking "Rav-Kav" activity data. "Rav- Kav" is a smart card used as a means of payment for public transportation in Israel. Travels in a private vehicle are monitored by linking a GPS device to the vehicle. The research team monitored the participants' travels for six months to learn their habits. After half a year of monitoring, participants became "Active" and received an initial budget. From that point on, for each ride participants made during peak hours to metropolitan areas, they had to pay a congestion charge funded from their initial budget. At the end of the year, the participants received payment according to their remaining final budget. The initial budget for each participant is fixed per year + a different supplement per operator. The initial budget is known to participants and has been updated on the operators' website and in the volunteer agreement.

As part of the experiment, the participants were asked to answer a questionnaire that included socio-demographic questions such as gender, residence, number of children, and profession. The questionnaires can help to learn about the participant's willingness to change travel patterns depending on their socio-demographic characteristics.

The current experiment began in mid-December 2021 and included 1455 participants. It lasted for 15 days- three weeks without weekends. The experiment participants were riders who were part of the "Derekh Erekh" project and had a personal "Rav-Kav." A personal "Rav Kav" is a card with the name and the card-holder's photo stamped on it. With this card, a person can redeem discounts for eligible individuals (youth, senior citizen, student) and purchase a monthly free pass. As noted, "Derekh Erekh" has access to all trips riders took on public transport using their personal "Rav-Kav." "Rav- Kav" card is not the only way to pay for using public transit in Israel; however, it is the most common way. The State Comptroller (2021) reports that 99% of public transit trips are via the "Rav-Kav" card. The participants chosen to participate in the experiment were riders that took at least one ride on public transit using their personal "Rav-Kav" between December 2020 and one month before the experiment started. Among 15000 riders participating in "Derekh Erekh," a total of 1455 were eligible to participate in the experiment. It is worth mentioning that it does not mean that the rest of the riders do not use public transit; they just do not use it by personal "Rav-Kav" whereas by other means of payment which the research team cannot monitor.

3.1 Data Sources

The paper uses three data sources; participants' trips by public transportation, participants' characteristics, and participants' trips by private vehicle.

While joining "Derekh Erekh," the participants consented to "Ayalon Highways" to monitor their travels by private and public transportation. Private vehicle travels are monitored by linking a GPS device to the participant's private vehicle. Public transport travels are only monitored if the participants made them by using a personal "Rav-Kav" card linked to the ID number. Data on public transport travels includes details about each trip a participant has made with "Rav- Kav" since joining "Derekh Erekh." Each trip has its time and date, unique route ID, departure station ID, and departure station location.

The second database used is based on the participants' characteristics. At the time of registration for "Derekh Erekh," each participant was asked to complete an baseline questionnaire. The questionnaire includes questions about the participant's gender, age, residence, employment status, marital status, employment sector, education, and number of children. Answering the questionnaire is mandatory to be eligible for payment upon completion of participation in "Derekh Erekh." However, the questionnaire can be filled out at any point and not necessarily at the time of joining. Therefore, some participants have not responded yet to the baseline questionnaire.

The third data set used is travels via private vehicle. Each trip has its time and date, origin and destination, velocity, duration, and congestion charge price. Through machine learning tools and the baseline questionnaire, participant's home polygon was found. After finding participant's home polygon ID, the list of characteristics was expanded to the socio-economic ranking and the quality of public transportation in the area.

Table 5 in the appendix shows descriptive statistics of participants' characteristics.

3.2 Allocation Mechanism

The participants were divided into six treatment groups and one control group. The allocation between treatment and control groups was not random, only within the treatment groups. According to "Derekh Erekh" rules, participants under "Monitor" status are not eligible to be assigned to a treatment group and receive a reward. The meaning is that all participants who joined the national trial during the last six months (June - December 2021) were automatically associated with the control group. To avoid a double incentive scheme, all treatment group participants had to become "Active" at least one month before the experiment started. Participants who became "Active" the month before the experiment began were removed from the trial. In addition, all the participants in the control group must have joined "Derekh Erekh" at least one month before the experiment started. Both conditions imply that nobody changed status from "Monitored" to "Active" during the experiment or the month prior it. Table 1 shows summary statistics of riding patterns before the experiment. The outcome variable is the cumulative number of days a participant used public transit during the three weeks before the experiment started. As can be seen, the distribution of number of the days using public transit is similar among all treatment and control groups. More details about the identification assumptions can be found in section 4.

The control group was composed of 264 participants. The remaining participants were assigned to the six treatment groups based on block randomization design. Block randomization is a commonly used technique in clinical trial design to reduce bias and achieve balance in allocating participants to treatment arms (Efird, 2011). The participants were divided into eight blocks based on three attributes.

- In the three weeks before the trial, has the participant used public transportation more than the public transportation usage median?
- Has the participant downloaded the app of "Derekh Erekh"? The basic assumption was that if a participant downloaded the application, it increased the chances for cooperation.

- Whether or not the participant lives in a polygon with high accessibility to public transportation. The public transport accessibility index for the home polygon was calculated based on three parameters:
  - Number of bus stops in the polygon.
  - The number of different bus routes that pass through the polygon.
  - The number of polygons can be reached via a direct bus or train route from the home polygon.

  Based on these three parameters, which assume the same importance, the accessibility index was calculated.

  $$index = \frac{e^{\beta*(log(Stops\ Number*Routes\ Number*Accessibility))}}{1+e^{\beta*(log(Stops\ Number*Routes\ Number*Accessibility))}} \tag{1}$$

  The actual value of the parameter β which was chosen to be 0.5, is not important. As long β is positive, which is a reasonable assumption, the function is monotonically increasing. The value of the index does not matter, only the order relative to other residence polygons index. After calculating the accessibility index of each participant by the residence polygon, the median was found. The median index determines whether the participant's residential polygon has high or low accessibility to public transport. Note that this index is different from the index shown in Table 5. The 'Public Transit Quality Index' in the Table 5 was received by the Ministry of Transport and Road Safety representatives after the trial ended.

The attributes used for the block design were chosen based on the prior assumption that the treatment effect within each group will depend on them. For example, we assumed that participants who use public transit regularly would react differently to the incentives than participants who never use public transit. Therefore, the experiment was designed to reduce bias and balance allocating participants into the six treatment groups. Within each block, each treatment arm had an equal number of participants assigned to it.

Table 1: Summary Statistics- Cumulative days of using public transit three weeks before treatment

Group	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Control	264	2.53	3.955	0	0	4	15
Payment 14	195	2.492	4.024	0	0	3	15
Payment 15	198	2.429	3.896	0	0	3	15
Payment 19	198	2.394	4.14	0	0	3	15
Payment 20	197	2.467	3.889	0	0	4	15
Payment 24	193	2.321	3.851	0	0	3	15
Payment 25	195	2.282	3.78	0	0	2.5	14

3.3 The incentives mechanism

As said before, the participants were divided into six treatment groups and one control group. Each treatment group received a different incentive in exchange for increasing public transportation usage. The daily incentive was given in exchange for making at least one trip on the same day by public transport. Participants in the control group were unaware of the experiment and did not receive any incentive in exchange for using of public transportation. Null hypothesis of the experiment is that the higher the daily incentive, the better the chance to change riding patterns and increase public transit usage. The daily payments were $\left\{14, 15, 19, 20, 24, 25\right\} NIS.$

The decision to create those specific groups was based on two factors. Firstly, we wanted a substantial gap between each group in order to capture the significance of the test. This is the reason for the 15, 20, and 25 payment groups. Secondly, we wanted to capture the power of the behavioral change to create a more continuous demand function. Thus, we also added 14, 19, and 24 payment groups. To be paired with the first three groups selected. We can deduce the marginal effect of adding 1 NIS by comparing them.

At the end of the trial, each participant received a gift card based on combination of the daily incentive and the cumulative number of days using public transit, and no more than 150 NIS.

$$Payment = min\left\{Daily\ Incentive * Number\ of\ Days, 150\right\} \tag{2}$$

A straightforward conclusion of the payment method is that after reaching the maximum payment limit, the participants lose the incentive to continue using public transit. However, analysis of travel patterns before the experiment showed that the vast majority of riders were not even close to reaching the payment ceiling and had to change their habits dramatically to gain the full payment. As seen in Table 1, participants belonging to the highest payment group, 25, have to increase their rides by 200% , on average, to reach the ceiling payment which is an ambitious goal.

3.4 Communication Mechanism

The communication with the participants was through SMS messages and by the official "Derekh Erekh" application. On Thursday night, three days before the experiment started, all participants in the treatment groups received a message with the experiment details. This was the first time they had heard about the upcoming experiment, and therefore could not change their patterns before it started. The message was different for each group according to the daily incentive. To avoid irrational behavior and bias in the experiment, participants were unaware that there were groups other than the group to which they were assigned.

During the experiment, the participants received a reminder message about the experiment each Saturday night before the beginning of a new week. The participants in the control group did not receive any messages and did not know they were participating in a sub-experiment of "Derekh Erekh."

4 Empirical Strategy

As presented in subsection 3.2, the allocation mechanism for treatment and control was not random. It was according to the participant's joining date to "Derekh Erekh." It is reasonable to assume that the joining date is a random variable and thus to see the allocation between all groups as a random allocation. However, for the completeness of the trial, several measures were taken to ensure an accurate and reliable estimation of the treatment effect.

First, the Kruskal-Wallis rank sum was performed. The goal was to examine if there were any differences between the treatment and the control groups before the experiment started. Kruskal-Wallis is a non-parametric test equivalent to one-way ANOVA. Instead of comparing population means, this method compares population mean ranks (i.e., medians). The test's null hypothesis is that the population medians are equal, versus the alternative that there is a difference between at least two of them (Bewick et al., 2004). Kruskal-Wallis Test was conducted to examine the differences in public transit usage. No significant differences ($\chi = 1.7$, p = .945, df = 6) were found among the 7 groups of participants (Control, Payment 14, Payment 15, Payment 19, Payment 20, Payment 24, Payment 25).

The test is not enough, though. It is possible that the differences in travel patterns between treatment and control groups were due to an eruption of a new COVID-19 wave (Figure 4 at the Appendix). It can be argued that participants in the treatment groups which are under "Active" status had stronger incentive to use public transportation despite the increase in morbidity compared to participants in the control group under "Monitor" status. Participants in the control group had no special incentive to travel by public transport during the trial, especially in light of the new COVID-19 wave. In contrast, the treatment group had a double incentive. The first incentive is to receive payment from the trial. The second incentive is to save the congestion charge that would have been paid if the participant had traveled in private. Therefore, examining the trends in public transit usage before the experiment is not satisfactory.

The relationship between the control and treatment groups at the end of the experiment was examined to address this claim. Suppose, indeed, there is a difference between the patterns of participants in light of the morbidity wave. In that case, it is expected that the gaps will be maintained even after the end of the experiment, at least to a lesser extent. It can be seen in Table 2 and Figure 1 that it is not the case. During the experiment period, gaps were created between the different groups. In contrast, immediately after the trial ended, all gaps vanished. These findings are also reflected in Table 2, which contains the regression results and examines the effect of the incentives on the treatment groups in relation to the control.

This means that if the increase in morbidity did not create differences between the groups after the end of the experiment, it can be concluded that it also did not constitute a decisive factor during the experiment. Therefore, the differences created between the groups can be attributed to the treatment effect and not to other external factors.

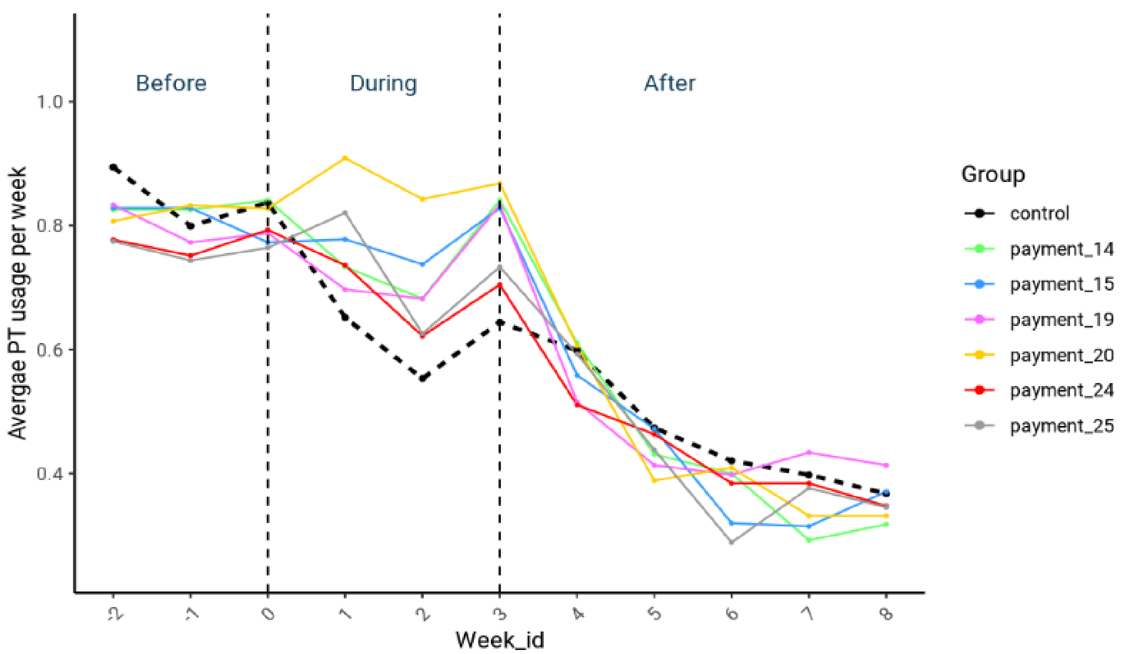

Figure 1: Travels by public transit before, during and after the experiment. Each dot represents the average number of days traveled by public transport in a specific week . $Weeks\ id = 1 - 3$ represent the average usage of public transit during the weeks of the trial

5 Results

5.1 Treatment Effect Estimation

There are many methods to estimate a causal effect. The most common model in social sciences is Difference-in-Differences (DID) (Roth et al., 2022). Chaisemartin and D'Haultfoeuille (2015) conducted a survey and found that 10.1% of all papers published by the American Economic Review between 2010 and 2012 use fuzzy DID designs. DID is used in observational studies where the assignments to the treatment and control groups are not necessarily random. DID is a quasi-experimental design that obtains an appropriate counterfactual to estimate a causal effect. DID is typically used to estimate the effect of a specific intervention or treatment by comparing the changes in outcomes over time between a population enrolled in the intervention group and a population that is not. The basic equation of the DID regression model is:

$$Y = \beta_0 + \beta_1 Time + \beta_2 Treatment + \beta_3 Time * Treatment + \beta^{\mathrm{T}} X \tag{3}$$

Where Y is the outcome of interest, Time is a dummy variable for the time point (Pre-treatment = 0, Post-treatment = 1), Treatment is a dummy variable for group assignment (Control = 0, Treatment = 1). Time*Treatment represents the interaction effect. The key identifying assumption for estimating the treatment effect is that the average outcome among the treatment and comparison populations would have followed "parallel trends" in the absence of treatment (Angrist and Pischke, 2009; Roth et al., 2022). In addition, there is an assumption that the treatment has no causal effect before its implementation (no anticipation). The treatment effect estimation in DID design is based on the structure of the linear model. One of the main assumptions of this model is that the outcome variable is normally distributed, and the relationship between the dependent variable and the independent variables is linear. The outcome variable of the current research is the number of days using public transit in a given period. The data set contains three time periods - before, during, and after the experiment. Each period lasted three weeks (excluding weekends), so for each individual i, at period t, the outcome variable ranged from 0 to 15, which contradicts the linear regression assumptions. Therefore, the treatment effect estimation must by using a nonlinear model.

When it comes to nonlinear estimation, the interpretation of the interaction parameter and DID model is not straightforward. Puhani (2008) has shown that the treatment effect on the treated in DID nonlinear model is:

$$\tau(Time=1, Treatment=1, X) = E(Y^1|Time=1, Treatment=1, X) - E(Y^0|Time=1, Treatment=1, X) = G(\beta_0+\beta_1+\beta_2+\beta_3+\beta^{\mathrm{T}}X) - G(\beta_0+\beta_1+\beta_2+\beta^{\mathrm{T}}X) \tag{4}$$

The treatment effect in Equation 4 is not equal to β_3 unless G is the linear function.

Moreover, Ai and Norton (2003) examined the interaction effect in nonlinear models. In the general case, the conditional mean of the dependent variable is:

$$E(Y|Time, Treatment, X) = G(\beta_0+\beta_1 Time+\beta_2 Treatment+\beta_{12} Time*Treatment+\beta^{\mathrm{T}}X) = G(\cdot) \tag{5}$$

Ai and Norton (2003) have showed that when G($\cdot$) = exp(β_0+β_1Time+β_2Treatment+β_{12}Time*Treatment+β^{T}X), the interaction effect is as follows:

$$\frac{\Delta^2 E(Y|Time, Treatment, X)}{\Delta Time \Delta Treatment} = \exp(\beta^{\mathrm{T}}X)\Big\{[\exp(\beta_1+\beta_2+\beta_{12}) - \exp(\beta_2)] - [\exp(\beta_1)-1]\Big\} \tag{6}$$

Ai and Norton (2003) state there are four implications of Equation 6 -

1. The interaction effect could be nonzero even if β_{12}=0
2. The statistical significance of the interaction effect cannot be tested with a simple t-test.
3. The interaction effect is conditional on the covariates.
4. The interaction effect may have different signs for different values of covariates.

To properly interpret the interaction effect and estimate the treatment effect, we will use difference-in-semielasticities (DIS) interpretation. Shang et al. (2017) define the difference-in-semielasticities (DIS) as the second explanatory variable's impact on the semielasticity of the dependent variable concerning the first explanatory variable. DIS is straightforward compared to other methods of interpreting and calculating the interaction effect, which is detailed in Ai and Norton (2003); Puhani (2008); Imbens and Athey (2006).

When the DIS is based on Equation 5 and $G(\cdot) = exp(\cdot)$, the calculation is as follows:

$$DIS = \frac{E(Y|Time = 1, Treatment = 1, X) - E(Y|Time = 0, Treatment = 1, X)}{E(Y|Time = 0, Treatment = 1, X)} -$$

$$\frac{E(Y|Time = 1, Treatment = 0, X) - E(Y|Time = 0, Treatment = 0, X)}{E(Y|Time = 0, Treatment = 0, X)} \tag{7}$$

$$= \exp(\beta_1 + \beta_{12}) - \exp(\beta_1)$$

The interpretation of the DIS is the difference between the average change rate among the treatment group, to the average change rate among the control group. Shang et al. (2017) suggested to estimate the DIS in three steps. First, estimating the coefficients β_1 to β_k by using Poisson Maximum Likelihood (PML) estimation. Second, calculating the DIS based on Equation 7. Third, estimating DIS standard error by using the Delta method. This framework provides a tractable and correct interpretation of the DID effect in terms of a DIS.

5.2 Quantitative results

To implement the DIS method mentioned above, Poisson maximum likelihood was estimated as follows:

$$(Number\ of\ days)_{it} = \exp(\beta_0 + \sum_{t=1}^{2} \beta_t Period_t + \sum_{g=1}^{6} \gamma_g Treatment_{ig} + \sum_{t=1}^{2}\sum_{g=1}^{6} \delta_{t,g} Period_t * Treatment_{ig} + a^T X_{itg} + \epsilon_{itg}) \tag{8}$$

Where Number of days_{it} indicates the number of days individual i travels by public transit at period t. Period_{t} is a dummy variable equal to 1 for period = t. For example, Period_1 equal to 1 at period "During" and 0 else. $\text{Treatment}_{\text{g}}$ is a dummy variable equal to 1 if individual i belongs to treatment group g and 0 else. Period_{t}*$\text{Treatment}_{\text{ig}}$ is the interaction and will be set to 1 only when both are set to 1. X_{igt} is a covariates vector representing individual i in group g at period t. The covariates are gender, residence, socio-economic ranking, public transit quality index, public transit using patterns, number of children, and more. ϵ_{itg} is a random Poisson distributed error. The coefficients of the model are easy to interpret. $100\beta_{\text{j}}$ is the semielasticity of $\text{E}(Y|X)$ concerning x_{j}: for small changes in $\Delta\text{x}_{\text{j}}$, the percentage change in $\text{E}(Y|X)$ is roughly $100\beta_{\text{j}}\Delta\text{x}_{\text{j}}$ (Wooldridge, 2002). The PML estimation for Equation 8 is presented in Table 2. The results show a positive and significant effect of the interactions between 'During' and each treatment group. However, as explained at Equation 6, the interaction effect resides in a nonlinear model, it is not equal to $\delta_{\text{t,g}}$ as one would have expected. This is why, the DIS was estimated as proposed in Equation 7. Each DIS was calculated separately. Each one refers to the difference between treatment group g and the the control group with respect to 'During' and 'Before' periods.

As can be seen, for all treatment groups the DIS is positive and significant. The interpretation of 'DIS Payment 14' is as follows: Assignment to treatment group 14 increases the semielasticity of public transit rides on period 'During' by 17.4%. In simpler terms, the difference between the average change rate of public transit ride days of treatment group 14, to the average change rate of the control group is equal to 17.4%. Looking at the DIS only might be misleading. A person looking at Table 2 results might deduce that participants who were assigned into one of the treatment groups had increased their travels by public transit during the experiment. However, this is not the case. When combining the regression results with Figure 1, it is easy to see that during the experiment, the average number of travel days among the control group dropped significantly compared to the weeks before. A plausible explanation is the effect of the new COVID-19 wave on public transit travels. During the experiment, the variance between all groups increased significantly compared to the weeks before and after. The increase in the variance, and the fact that all treatment groups have seen less reduction in travels, is attributed to the treatment effect. Although the amount of travels did not increase as we might expect, it can be seen that the deterioration rate was lower. Had the experiment not been conducted, we would have expected the trends in all treatment groups to be identical to the control group. It can also be seen that immediately after the experiment, the variance between all groups had reduced, and the travel patterns returned to be similar.

Examining control group decrease source reveals that both number of riders and rides dropped sharply during the experiment. Number of riders is defined as the number of participants who had at least one ride using public transit. Compared to the three weeks before the experiment, the number of riders among the control group has dropped by 30%. The drop did not consider ”New Joiners”, meaning participants who did not use public transit three weeks prior to the trial, and begun usage during the trial. In addition, participants who used public transit before the experiment and continued to do so, decreased their rides via public transit by 15% on average.

A null hypothesis of the experiment was that the higher the daily incentive, the better the chance to change riding patterns and increase public transit usage. A surprising result of the experiment is the absence of monotony in the treatment effect. Plausible explanation might be the limit for maximum overall payment. It can disrupt incentives and decision-making during the trial. It can be argued that participants in groups with higher daily payment have the opportunity to reach the maximum payment faster and lose the incentive to travel by public transport in the rest of the trial. However, examination of the results shows that the change in behavior among groups 24 and 25 brought only a few participants to the maximum level of incentives, i.e., it does not appear that the payment ceiling was indeed an effective barrier and disrupt the monotony effect we expected to see. In addition, an analysis of the behavioral patterns of participants who

Table 2: PML Estimation

	Dependent variable:
	Number of days
During * Payment_14	0.215** (0.106)
During * Payment_15	0.278*** (0.103)
During * Payment_19	0.235** (0.096)
During * Payment_20	0.374*** (0.100)
During * Payment_24	0.196** (0.097)
During * Payment_25	0.268*** (0.103)
After * Payment_14	−0.020 (0.133)
After * Payment_15	−0.064 (0.152)
After * Payment_19	−0.062 (0.134)
After * Payment_20	−0.030 (0.134)
After * Payment_24	−0.023 (0.135)
After * Payment_25	−0.015 (0.137)
DIS Payment_14	0.174*** (0.073)
DIS Payment_15	0.234*** (0.076)
DIS Payment_19	0.193*** (0.075)
DIS Payment_20	0.331*** (0.08)
DIS Payment_24	0.157** (0.075)
DIS Payment_25	0.224*** (0.078)
Covariates	Yes
Observations	4,309
Log Likelihood	−9,052.851
Akaike Inf. Crit.	18,169.700
Note:	*p<0.1; **p<0.05; ***p<0.01
	Clustered standard errors at Rider level

reached the maximum ceiling shows that even after losing the marginal incentive to travel, those participants continued to use public transportation. Based on the current experiment, there is no evidence that after reaching the incentive ceiling, there is a halt in the use of public transport. The short length of the experiment, which may have been a limitation, should be noted. Most participants reached the maximum payment in the last week of the experiment, therefore there was not necessarily enough time to examine the differences in behavior change among those who achieved the goal.

An opposite claim is that participants in lower payment groups had to use public transportation many times to reach the payment limit, therefore we can expect to see monotony in the other direction. Meaning, the lower the daily incentive, the better the chance to change riding patterns. However, although groups 14 and 15 supposedly had to use public transport many times to reach the payment cap, this was not reflected in the results. Probably, the daily incentives to do so were not high enough to incentivize the participants.

We believe there are two main reasons why the treatment effect is not monotonous. First, the length of the experiment, as explained before. Second, the effect of the new COVID-19 wave. The increase in morbidity added a dimension of uncertainty and sharpened the heterogeneity between individuals in how they responded to the increase in morbidity and the effect of the incentives.

Although the treatment effect did not appear as monotonous as we expected, it is interesting to examine the differences between the subgroups as described in subsection 3.2. It can be seen that there is actually a monotony effect among each of the subgroups. The treatment effect is greater for group 15 over group 14, group 20 over group 19 and group 25 over 24. The differences within each sub-groups are not significant. However, the rounding of 1 NIS of the daily amount seems to have some psychological effect on the participants.

5.3 Substitution between public transit and private vehicles

One of the study's main goals is to examine the substitutability between public transportation and private vehicle. We assume that the monetary incentives will increase public transportation and reduce private vehicle usage. To test this claim, an analysis was performed in two stages. First, the participants were classified into two groups according to the change of public transportation usage compared to the control group. For each participant, the difference in the number of traveling days by public transport during and before the experiment was calculated. Then, the average difference between the control and treatment groups was calculated, as well. That is, the difference between how many treatment group participants changed their trips compared to the control group participants. Participants who belonged to a treatment group and whose travel differences were greater than the difference between the treatment group and the control group, were classified as the "Increased" group. The rest of the participants were classified into the "Decline / Same patterns" group. Second, after the classification, the DIS method was implemented once again, using Poisson maximum likelihood estimation. In this subsection, the analysis is performed without separation between the various treatment groups, only between participants in the control group to participants in one of the treatment groups. The estimation equation is as follows:

$$(Number\ of\ rides)_{it} = \exp(\beta_0 + \beta_1 Period_t + \beta_2 Increased_i + \beta_3 Period * Increased_{it} + \beta^T X_{it} + \epsilon_{it}) \quad (9)$$

Where Number of rides_{it} indicates the number of rides an individual i travels by private vehicle at period t. Period_t is a dummy variable equal to 1 for period = "During". $\text{Increased}_\text{i}$ is a dummy variable equal to 1 if individual i increased public transit usage compared to the control group during the experiment. Period_t*$\text{Treatment}_{\text{ig}}$ is the interaction effect, X_{it} covariates vector of individual i at period t. The covariates are gender, socio-economic ranking, public transit quality index, age and more. ϵ_{it} is a random Poisson distributed error.

Table 3 shows the estimation results. The first column is for the total sample, and the second and the third are for males and females separately. The heterogeneity analysis, in sub-section 5.4, shows that males responded to the experiment stronger than females. Therefore, perhaps we will see similar differences between males and females in private vehicle patterns. According to the results in Table 3, it seems that both males and females, who increased the number of their trips by public transportation, decreased their private vehicle usage during the experimental period. Furthermore, for both genders, the DIS is approximately the same and equal to 5.3%. This means that participants who increased public transportation usage, decreased by 5.3% the number of trips by private vehicle, compared to participants who did not change public transit travel patterns.

The analysis shows that there is a certain degree of substitutability between public transport and private vehicle. This means that providing incentives that encourage public transport travels,

Table 3: Private vehicle substitution

	Dependent variable: Vehicle rides		
	Total	Males	Females
	(1)	(2)	(3)
Age	0.009*** (0.003)	0.008** (0.004)	0.017** (0.007)
Socio economic ranking	−0.051*** (0.008)	−0.056*** (0.009)	−0.034* (0.017)
PT quality index	−0.002*** (0.001)	−0.001* (0.001)	−0.003** (0.001)
During	0.012 (0.021)	0.009 (0.022)	0.021 (0.053)
Female	−0.038 (0.044)		
Increased	0.015 (0.041)	−0.044 (0.046)	0.240*** (0.089)
During x Increased	−0.054** (0.024)	−0.053** (0.027)	−0.055 (0.058)
Constant	3.864*** (0.134)	3.943*** (0.146)	3.346*** (0.269)
DIS	-0.053*** (0.013)	-0.052*** (0.015)	-0.054* (0.031)
Observations	3,517	2,791	726
Log Likelihood	−43,596.360	−35,550.800	−7,835.698
Akaike Inf. Crit.	87,214.720	71,119.600	15,689.400
Note:			*p<0.1; **p<0.05; ***p<0.01

helps to road congestion by reducing the demand for private vehicle. It is important to remember that the experiment lasted for a short period of time, with a significant increase in morbidity from COVID-19. Therefore, if the experiment was in different time or situation, we would have expect to see even stronger results.

5.4 Heterogeneity Analysis

Estimating the average treatment effect has great importance and influence on policymakers, but alone is not enough. Many characteristics can have an impact on the degree of response to incentives. For example, gender, income, accessibility and quality of public transportation, flexibility at working hours, parking space at the workplace and more. Each of these examples can affect the use of public transportation and response to the incentives given in the experiment. When making a policy decision about changing priorities and allocating resources it is important to consider these factors. For example, suppose it turns out that people who do not have a reserved parking space in their workplace have responded better to incentives and increased use of public transportation. In that case, the government may want to apply parking taxation policies alongside with improving public transportation quality. Alternatively, if the parking space does not affect public transit usage, it may not be necessary to impose the parking taxation policy and increase the tax burden. Naturally, it is not possible to examine all of these characteristics, some of which are not in our possession and some of which are difficult to quantify.

The heterogeneity analysis was performed by adding an interaction dimension to the standing method described in the subsection 5.1. Instead calculating the DIS as in Equation 7, we added a dummy variable D as an additional interaction which is a heterogeneity characteristic. The new DIS calculation is the difference-in-differences of the DISs:

$$\begin{aligned} DIS = DIS_{\mathrm{D=1}} - DIS_{\mathrm{D=0}} = \Big(& \frac{E(Y|Time=1, Treatment=1, D=1, X) - E(Y|Time=0, Treatment=1, D=1, X)}{E(Y|Time=0, Treatment=1, D=1, X)} - \\ & \frac{E(Y|Time=1, Treatment=0, D=1, X) - E(Y|Time=0, Treatment=0, D=1, X)}{E(Y|Time=0, Treatment=0, D=1, X)} \Big) \\ -\Big(& \frac{E(Y|Time=1, Treatment=1, D=0, X) - E(Y|Time=0, Treatment=1, D=0, X)}{E(Y|Time=0, Treatment=1, D=0, X)} - \\ & \frac{E(Y|Time=1, Treatment=0, D=0, X) - E(Y|Time=0, Treatment=0, D=0, X)}{E(Y|Time=0, Treatment=0, D=0, X)} \Big) \end{aligned} \tag{10}$$

In this section, the heterogeneity analysis is performed without separation between the various treatment groups, only between participants in the control group to participants in one of the treatment groups. The reason is that examining the characteristics of the individuals in each treatment group separately will cause a too small sample that does not represent the population and does not allow inference and causality to be drawn. The heterogeneity analysis in this research is based on the following characteristics:

- **Gender** - Examining the differences between males and females in response to the experiment incentives.

- **Socioeconomic ranking** - Examining the differences between people who live in a place with high and low socioeconomic ranking. For each participant with a known place of residence the socioeconomic ranking was matched based on the Israeli Central Bureau of Statistics data. Then, the participants were divided into two groups by the median socioeconomic ranking.

- **Public transit patterns (PT patterns)** - The number of travels using 'Rav Kav' six months before to the trial was measured. Then, for each participant, the average travel days in a week was calculated. Afterward, based on the median value of the entire group, each participant was assigned to either 'high' or 'low' usage group.

- **Private Vehicle habits** - The same as above. The division into two groups of 'high' or 'low' usage was based on private vehicle usage six months prior to the experiments. The average travel days in a week were calculated for each participant. Afterward, based on the median value of the entire group, each participant was assigned to either 'high' or 'low' usage group.

- **Public Transit Quality Index (PT Index)** - The index represents the quality of public transportation in each polygon. The index received directly from the Ministry of Transportation after the experiment ended and is different from the index described in sub-section 3.3. The index ranges from 1 to 100 and is based on the weighed attributes score- availability, reliability, and accessibility. The participants were divided into two groups 'high' or 'low' index, based on the median value of the entire sample.

The full results can be found in Table 6 in the Appendix. The focus in this sub-section is on characteristics with significant results. Those characteristics are Gender and Public transit patterns. As seen in Table 4 males and participants with low habits of public transit usage responded stronger to incentives.

Table 4: Heterogeneity Analysis - Gender and Public Transit Patterns

	Dependent variable:	
	count_day_rides	
	PT patterns	Gender
	(1)	(2)
Female	-0.031 (0.095)	-0.105 (0.248)
High PT patterns	2.665*** (0.247)	3.312*** (0.121)
Treatment	-0.465^{*} (0.281)	-0.049 (0.143)
During * Treatment	1.203** (0.534)	0.308*** (0.097)
After * Treatment	0.716 (0.809)	-0.013 (0.127)
During * High PT patterns	1.120** (0.510)	
After * High PT patterns	1.609** (0.755)	
Treatment * High PT patterns	0.494* (0.296)	
During * Treatment * High PT patterns	-1.015^{*} (0.540)	
After * Treatment * High PT patterns	-0.862 (0.816)	
During * Female		0.058 (0.179)
After * Female		0.222 (0.227)
Treatment * Female		0.224 (0.269)
During * Treatment * Female		-0.367^{*} (0.194)
After * Treatment * Female		-0.389 (0.254)
Constant	-1.140^{***} (0.253)	-1.741^{***} (0.191)
$DIS_{D=1}$-$DIS_{D=0}$-	-0.44** (0.199)	-0.32*** (0.134)
Covariates	Yes	Yes
Observations	3,571	3,571
Log Likelihood	$-7{,}475.923$	$-7{,}476.571$
Akaike Inf. Crit.	14,999.850	15,001.140
Note:		*p<0.1; **p<0.05; ***p<0.01

For both, gender and Public transit patterns, the diff-in-diff DISs are negative and significant. It means that participants with low public transit habits which assigned to the treatment group responded more to incentives than their counterparts in the control group, and relative to participants with high public transit habits in the treatment group. The same interpretation is for gender - males in the treatment group responded more to the incentives than their counterparts in the control group, and relative to females in the treatment group. The effect of the diff-in-diff DIS for PT patterns is greater than the effect for gender. However, this is mainly due to the fact that participants with low habits rarely use public transportation and even the slightest change in their behavior seems to be most significant when looking at it in percentages. When examining the gender differences interesting results are obtained. Both Table 4 and Figure 2 show that during the trial period males in the treatment group increased their travels by public transit relative to the weeks preceding it. In contrast, females in the treatment group significantly reduced their travels similar to the behavioral patterns in the control group. This trend is not only characterized by the aggregate view of the whole treatment group together, but is reflected in each treatment group separately, as can be seen in Figure 3 in the Appendix. In fact, it seems that on average, females were not affected at all by the incentives compared to males who were significantly affected.

There may be many reasons for the gender differences phenomenon. Those are interesting to explore in further research dealing with gender differences and the impact of economic incentives, particularly under the framework of public transport travel habits.

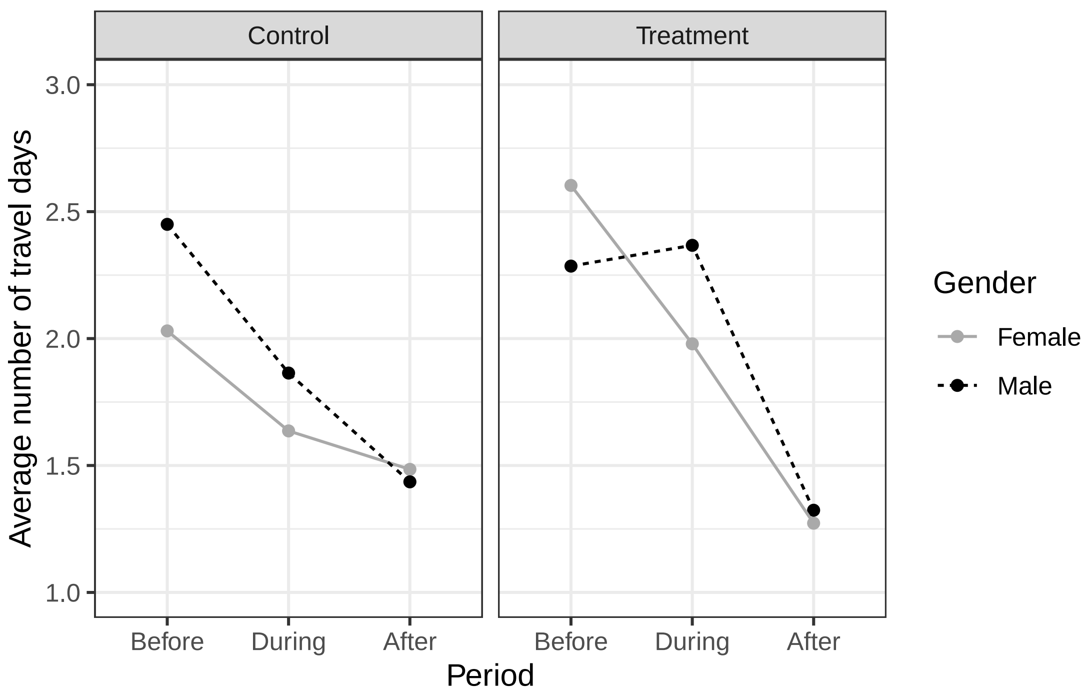

Figure 2: Traveling patterns by public transit by group, period and gender. Each period represents 3 weeks of average travel days.

6 Conclusion

The study shows evidence of the effect of monetary incentives on public transport travel patterns. In the experiment, 1455 participants were divided into six treatment groups and one control group. Their habits were examined before, during, and after the experiment. For each day of using public transit, participants in the treatment groups received a daily incentive in accordance with the allocation. At the end of the experiment, the participants received a gift card worth the amount they have accumulated over the three weeks, but no more than 150 NIS. Before the experiment, three hypotheses were suggested. First, monetary incentives will have a positive effect on public transport travel habits. Second, we will see some long-lasting effect. Third, there will be substitution between public transit and private vehicle. During this study, we tried to examine these three assumptions.

First, although the trial took place in the shadow of a renewed increase in the number verified to COVID-19, the monetary incentives appeared to have a positive effect on public transport travel habits for all treatment groups. By using the DIS method, on average, treated participants increased by 21.8% their usage of public transportation compared to participants in the control group. Even though a positive effect of the incentives has been found, a monotonic effect was not identified. It is possible that in a longer experiment, without a limit on the overall payment, the differences between the groups would have been amplified.

Second, after the trial ended, several phenomena were witnessed. First, public transportation usage across all the treatment groups has been identified with the control group. Second, all groups have shown a sharp decrease in public transit usage. A plausible explanation for this outcome is due to the spread of the COVID-19 variant. It led to an increase in morbidity, quarantines and staying at home for work. It is possible that in light of the short duration of the experiment, even without the effect of the disease, it would have been difficult to identify the experiment's long-term effect. However, this cannot be determined with certainty, thus making it a further research topic.

Third, our estimates suggest that participants who increased their usage of public transit, reduced their use of private vehicles by 5.3% compared to participants who did not change their public transit patterns. This result is also valid when sub-dividing into male and female.

Another component of the study was the heterogeneity analysis and the examination of the experiment's effect on participants with different characteristics. The most significant difference identified is the gender gap. It appears that across all treatment groups, females did not respond to the incentives, and their travel trends were identical to their counterparts in the control group. In contrast, during the trial, the males increased their public transit usage significantly. While the gender gap was wide during the trial, it surprisingly shrank after the trial ended, resulting in no difference in the corresponding groups.

In conclusion, the experiment has shown that monetary incentives positively affect travel patterns in public transport, especially for males. However, to increase the certainty of these findings, further research needs to be conducted. Open questions such as what are the long-lasting effects of positive monetary incentives, and what are the causes of the gender gap are yet to be revealed. These analyzes can help future policymakers determine how to allocate resources in order to improve public transportation and establish appropriate infrastructure.

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Appendices

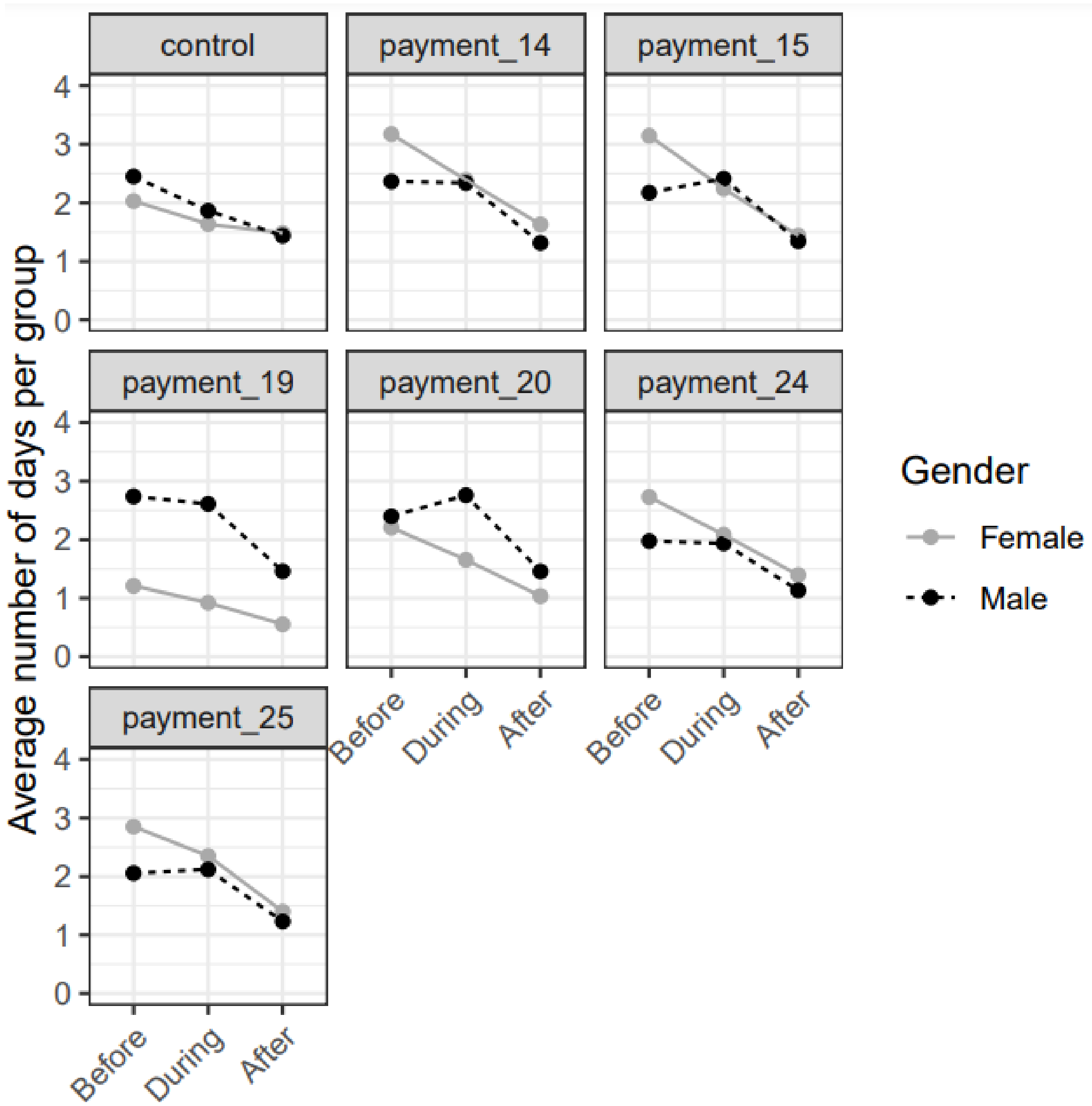

Figure 3: Gender Differences Analysis. Traveling patterns by public transit by assignment, period and gender. Each period represents 3 weeks of average travel days.

Table 5: Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 50	Pctl. 75	Max
Gender	1209							
... Female	309	25.6%						
... Male	900	74.4%						
Age	376	35.652	9.439	21	30	33	38	75
Marital_status	841							
... Divorced	12	1.4%						
... In relationship	87	10.3%						
... Married	490	58.3%						
... Single	252	30%						
Kids_num	377	0.928	1.228	0	0	0	2	6
Education	841							
... Academic	595	70.7%						
... Post Secondary	130	15.5%						
... Secondary	116	13.8%						
Sector	648							
... academy	38	5.9%						
... Other	174	26.9%						
... Commerce	21	3.2%						
... Education	21	3.2%						
... finance	54	8.3%						
... High tech	221	34.1%						
... Industry	45	6.9%						
... Public sector	74	11.4%						
Work_status	840							
... Emp. full-time	621	73.9%						
... Emp. half-time	98	11.7%						
... Non-working	47	5.6%						
... Self-employed	44	5.2%						
... Shifts	30	3.6%						
Living_area	1389							
... Other	699	50.3%						
... Ashdod	42	3%						
... Be'er Sheva	41	3%						
... Bet Shemesh	33	2.4%						
... Coastal plain	42	3%						
... Hadera	37	2.7%						
... Haifa	48	3.5%						
... Jerusalem	77	5.5%						
... Netanya	40	2.9%						
... Periphery	59	4.2%						
... Petah Tiqwa	48	3.5%						
... Ramat Gan	37	2.7%						
... Rehovot	42	3%						
... Rishon LeZiyyon	60	4.3%						
... Tel Aviv - Yafo	84	6%						
Socio Economic Ranking	1454	6.061	2.094	1	5	6	8	10
Public Transit Quality Index	1379	64.649	24.854	0	51.572	71.801	84.799	96.694
Average Number of Weekly Trips (by Car)	1201	15.527	8.357	0	9.875	14.75	20.125	56.75

Table 6: Heterogeneity Analysis

	Socio	Vehicle patterns	PT quality index	PT patterns	Gender
During	-0.278^{***} (0.086)	-0.301^{**} (0.149)	-0.236^{**} (0.113)	-1.344^{***} (0.504)	-0.273^{***} (0.088)
After	-0.488^{***} (0.105)	-0.540^{**} (0.244)	-0.347^{**} (0.149)	-2.037^{***} (0.749)	-0.534^{***} (0.113)
Post.Secondary	−0.174 (0.146)	−0.180 (0.145)	−0.175 (0.146)	−0.173 (0.146)	−0.173 (0.146)
Secondary	−0.017 (0.141)	−0.016 (0.141)	−0.014 (0.142)	−0.017 (0.141)	−0.017 (0.142)
Single	0.059 (0.113)	0.062 (0.112)	0.057 (0.113)	0.060 (0.113)	0.060 (0.113)
In.relationship	0.029 (0.161)	0.056 (0.162)	0.032 (0.161)	0.032 (0.161)	0.031 (0.161)
Female	−0.032 (0.095)	−0.043 (0.096)	−0.034 (0.095)	−0.031 (0.095)	−0.105 (0.248)
High PT patterns	3.313^{***} (0.121)	3.305^{***} (0.121)	3.313^{***} (0.121)	2.665^{***} (0.247)	3.312^{***} (0.121)
Low vehicle patterns	−0.121 (0.093)	0.009 (0.254)	−0.123 (0.093)	−0.122 (0.093)	−0.122 (0.093)
Low socio economic	−0.148 (0.299)	-0.185^{*} (0.097)	-0.176^{*} (0.098)	-0.173^{*} (0.098)	-0.173^{*} (0.098)
Treatment	0.009 (0.141)	0.079 (0.206)	0.138 (0.187)	-0.465^{*} (0.281)	−0.049 (0.143)
PT index - Above median	0.018 (0.087)	0.014 (0.087)	0.098 (0.230)	0.020 (0.088)	0.020 (0.087)
During * Treatment	0.263^{***} (0.095)	0.265^{*} (0.156)	0.131 (0.123)	1.203^{**} (0.534)	0.308^{***} (0.097)
After * Treatment	−0.073 (0.121)	−0.011 (0.254)	-0.351^{**} (0.165)	0.716 (0.809)	−0.013 (0.127)
During * Low socio economic	0.104 (0.187)				
After * Low socio economic	0.104 (0.279)				
Treatment * Low socio economic	0.014 (0.311)				
During * Treatment * Low socio economic	−0.184 (0.203)				
After * Treatment * Low socio economic	−0.203 (0.298)				
During * Low vehicle patterns		0.253 (0.171)			
After * Low vehicle patterns		0.276 (0.270)			
Treatment * Low vehicle patterns		−0.159 (0.266)			
During * Treatment * Low vehicle patterns		−0.245 (0.185)			
After * Treatment * Low vehicle patterns		−0.358 (0.288)			
During * PT index - Above median			0.105 (0.153)		
After * PT index - Above median			−0.159 (0.225)		
Treatment * PT index - Above median			−0.191 (0.247)		
During * Treatment * PT index - Above median			0.035 (0.167)		
After * Treatment * PT index - Above median			0.376 (0.245)		
During * High PT patterns				1.120^{**} (0.510)	
After * High PT patterns				1.609^{**} (0.755)	
Treatment * High PT patterns				0.494^{*} (0.296)	
During * Treatment * High PT patterns				-1.015^{*} (0.540)	
After * Treatment * High PT patterns				−0.862 (0.816)	
During * Female					0.058 (0.179)
After * Female					0.222 (0.227)
Treatment * Female					0.224 (0.269)
During * Treatment * Female					-0.367^{*} (0.194)
After * Treatment * Female					−0.389 (0.254)
Constant	-1.774^{***} (0.194)	-1.818^{***} (0.238)	-1.838^{***} (0.221)	-1.140^{***} (0.253)	-1.741^{***} (0.191)
Observations	3,571	3,571	3,571	3,571	3,571

Figure 4: Daily New Cases COVID-19