The Impact of High-Occupancy Vehicle Lanes on Commuters: Field Evidence

Maxime C. Cohen
Desautels Faculty of Management, McGill University, maxime.cohen@mcgill.ca

Avia Ratzon
Google/Waze, Tel Aviv, Israel, aviar@google.com

Roy Sasson
Google/Waze, Tel Aviv, Israel, rsasson@google.com

Governments are actively investing to alleviate traffic congestion. Starting from the 1970s, a common policy has been to introduce high-occupancy vehicle (HOV) lanes, that is, traffic lanes exclusively reserved for vehicles with more than one occupant. Following the introduction of HOV lanes in several countries, their effectiveness has been the topic of heated debates. In this paper, we have a unique opportunity to empirically examine the impact of introducing HOV lanes on carpooling. In October 2019, the Israeli government has decided to introduce three HOV lanes. In this context, we have access to traffic and carpool data—from Waze (the free GPS navigation app owned by Google)—both before and after introducing the HOV lanes. We can thus rigorously quantify the impact of introducing an HOV lane on carpool intent and adoption. We also study refined questions around the effectiveness of different types of HOV lanes (2+ versus 3+), the impact at different times of the day, and the behavioral effect on commuters (e.g., strategically adapting commute times). Our study shows that the introduction of the HOV lanes led to a median time saving during rush hours of 5.7–15.7 minutes and increased the carpool rates by hundreds of percent for some routes. Interestingly, we find that the new HOV lanes have a global impact as they also raised the carpool rates for routes unaffected by the HOV lanes. This effect can be explained by the increased awareness of the public about the opportunity of carpooling.

Key words: Carpooling, Public Policy, Natural Experiment, Reducing Commute Time.

1. Introduction

High-occupancy vehicle (HOV) lanes are traffic lanes that can be used only by vehicles with more than one occupant (e.g., buses and carpoolers). HOV lanes (or some close variation) have been implemented across six continents. The primary purpose of HOV lanes is to increase the average vehicle occupancy and ultimately reduce traffic congestion and air pollution.

While several government entities and researchers are convinced about the benefits of HOV lanes, many others are questioning their efficacy (see, e.g., Wiseman 2019, and the references therein). A common critique claims that HOV lanes are underused and do not balance the additional congestion created in non-HOV lanes, so that the high infrastructure cost is not justified. HOV lanes have also

raised social problems. A notorious example was in Indonesia, where a number of Indonesians saw an opportunity in HOV lanes and became "car jockeys." These people made a living by offering drivers to ride their vehicles (in exchange for payment) to help meet the HOV lane's occupancy limit (while also letting parents earn money from their babies as additional passengers). This issue culminated in 2016, when the "3-in-1" rule (to use HOV lanes) was suspended in Jakarta and replaced by an "odd-and-even" license plate number system.

Still, in many countries, HOV lanes have remained a popular government policy to alleviate traffic congestion. According to data from the U.S. Office of Highway Policy Information, in 2006, the HOV lanes covered a total of 1,745.14 miles across the United States. Several studies have examined the HOV lanes' efficacy by running surveys and measuring the rate of use (or non-use) of the HOV lanes. This paper contributes to this stream of research by investigating the impact of three newly built HOV lanes in Israel, while mainly focusing on carpool intent and adoption.

Israel has been concerned with the low average occupancy per vehicle on the road, as stated in a recent Times of Israel article: "According to Ministry of Transportation data, private vehicles in Israel carry an average of 1.2 people (driver included), while the average in other OECD countries is between 1.6 and 1.8 occupants per vehicle."[1] In response, the Israeli government has decided to introduce three HOV lanes. More precisely, as of October 4, 2019, vehicles with more than one person (i.e., 2+) will be allowed to use an HOV lane on a 30-kilometer stretch on Route 2 between Tel Aviv and Netanya (in both directions), and vehicles with at least three occupants (i.e., 3+) will be able to use an HOV lane on a 22-kilometer stretch of the Ayalon highway. These three HOV lanes were strategically deployed in routes with a high level of traffic (i.e., starting from dense living areas and ending in the center of the country where many individuals need to commute daily). Interestingly, the efficacy of these HOV lanes is the topic of many heated debates both in the Israeli news and politics. While the Israel ministry of transportation qualifies the policy as a success,[2] it is not hard to find opposite appraisal. For example, several media articles accuse the new HOV lanes to lengthen travel times and to create chaos.[3] While both sides may have legitimate arguments, formal data-driven analyses are needed in order to carefully assess the impact of these new HOV lanes on carpool intent and adoption, which is the focus of this paper.

1.1. Setting and Research Questions

Our goal is to carefully examine the impact of introducing the three HOV lanes in Israel in October 2019. We have a unique opportunity to leverage a comprehensive dataset from Waze. In addition

[1] https://www.timesofisrael.com/israel-unveils-first-ever-carpool-lanes-in-bid-to-ease-crippling-congestion/

[2] https://www.calcalistech.com/ctech/articles/0,7340,L-3771641,00.html

[3] https://en.globes.co.il/en/article-israel-carpool-lanes-proving-a-disaster-1001304806

to the Waze traffic data, we also have access to carpool data from the Waze carpool platform.[4] This platform mainly focuses on helping commuters find carpool rides, making it a great fit to the context of our study. Users can register as drivers or riders and are matched to other users with similar commuting patterns. Subsequently, users can send offers to each other to share a ride. The platform takes care of tradeoffs between rider walking and driver detour, handles payments, and proposes optimized pick-up and drop-off locations.

While our data is far from including each and every vehicle on the road, we believe that it is a good representation of the overall picture. In fact, the majority of Israeli commuters routinely use the Waze GPS navigation app. As of February 2020, using Waze data, we record more than 4 million monthly Waze users in Israel. The Israeli population is estimated to be around 9 million, and the number of registered vehicles around 3.5 million.[5] These numbers provide clear evidence that a large number of Israeli commuters are using Waze. To our knowledge, this paper is among the most comprehensive studies aiming to examine the impact of an HOV lane on carpool intent and adoption. Furthermore, since most of the HOV lanes were built more than a decade ago, it is hard to compare the data before and after introducing the HOV lane. In our case, however, we have access to traffic and carpool data both before and after the policy change—allowing us to cast this event as a natural experiment. Using our data, we proceed by carefully selecting a sample of routes which are the most affected by the HOV lanes. We then select control routes to form appropriate benchmarks (see more details in Section 3.4). We aim to address the following questions:

- Did the treatment actually take place? In other words, are commuters using the HOV lanes and does it allow them to save time on their commute?
- What is the impact of introducing the HOV lanes? Does the introduction of the HOV lanes increase the number of carpool rides? If yes, by how much and under what conditions?
- Are there any interesting differences among the three HOV lanes? Recall that two HOV lanes require at least two occupants, whereas the third one imposes a minimum of three occupants. Which requirement is more successful?

Finally, we use our results to draw behavioral and policy implications. For example, we investigate whether commuters strategically adapt their commute time (e.g., by leaving earlier than before) in anticipation to a higher level of traffic due to the new HOV lane.

1.2. Summary of Results

Our goal is to infer the impact of the HOV lanes on carpool intent and adoption. To guide our analysis, we carefully select a sample of routes which are supposed to be affected by the HOV lanes

[4] https://www.waze.com/carpool

[5] https://www.ceicdata.com/en/israel/number-of-registered-motor-vehicles

(treated routes). We then select similar routes which are not supposed to be affected by the HOV lanes (control routes).

We first validate the fact that the treatment did take place. Namely, we observe that commuters are using the HOV lanes and earn a median time saving during rush hours of 8.1, 5.7, and 15.7 minutes across the different HOV lanes. We then compare the carpool intent and adoption of commuters before and after introducing the HOV lanes. For all three HOV lanes, we find that the number of sent offers by drivers (via the Waze carpool platform) increases significantly after the policy change. This shows that drivers are indeed reacting to the new HOV lanes. They become more interested in carpooling and are willing to make the effort to reach out to potential riders. At the same time, the number of offers sent by riders is not significantly affected by the policy change. This is inline with the fact that the policy is mainly targeted to affect drivers.

For the two HOV lanes with a 2+ requirement, we also find that the number of completed carpools increases (it increased by hundreds of percent for some routes). This confirms the fact that drivers are able to find a rider, so that the demand side of the market in these routes is liquid enough. For the third HOV lane—which requires at least three occupants—we find that the number of carpool rides does not increase despite the increased number of sent offers by drivers. This conveys that it is not easy for drivers to find two distinct riders. Even tough the number of sent offers by drivers increases, the number of cancellations also increases so that most of the drivers who are interested in carpooling do not end up not sharing a ride. Ultimately, this suggests that the market dynamics plays an important role when deciding the requirement of an HOV lane. In our data, a 2+ requirement was more successful than a 3+ requirement in terms of completed carpools. Interestingly, we find that the new HOV lanes have a global impact as they also raised the carpool rates for routes unaffected by the HOV lanes. This effect can be explained by the increased awareness of the public about the opportunity of carpooling. Finally, we observe that commuters anticipate the increased level of traffic and respond by strategically adapting their commute time. Such time spillover effects can play a critical role in alleviating traffic congestion and can have interesting policy implications.

2. Literature Review

Since the seminal work by Vickrey on congestion pricing (Vickrey 1969, 1963), research on public policies for traffic congestion has proliferated. At a high level, Vickrey proposed to use dynamic pricing to balance supply and demand by discouraging certain users to access congested roads during peak-demand times. Cities such as London and Singapore have implemented programs based on this principle. In the last four decades, various alternative policies to reduce traffic congestion have been proposed including restricted days, adding bus lanes, making public transportation free, and introducing HOV lanes.

Several studies have examined the effectiveness of HOV lanes. For example, an overview of the descriptive performance of several HOV lanes across North America is presented in Wellander and Leotta (2000). Yet, the debate of whether HOV lanes are effective at reducing traffic congestion and at convincing solo car drivers to carpool is still open. On the one hand, researchers have identified instances where HOV lanes can be quite beneficial. Poppe et al. (1994) found that HOV lanes in the Phoenix, Arizona metropolitan area are effective in periods of high congestion. Martin et al. (2004) conducted a similar analysis in Salt Lake Valley, Utah and found similar results. Boriboonsomsin and Barth (2007) studied the effectiveness of HOV lanes across California using peak hour traffic data from more than 700 stations. The authors found that HOV lanes are under-utilized and led to small travel time savings (which are not enough to incentivize users to carpool). Using survey data, Giuliano et al. (1990) compared the Route 55 HOV in California to a control group of freeway commuters. The authors showed that only the carpool rate for peak period commuters has increased. On the other hand, one can also find a number of papers that support the argument that HOV lanes are not effective (see, e.g., Dahlgren 1998, Shewmake 2012, Wiseman 2019). These papers claim that HOV lanes are underused and do not balance the additional congestion created in non-HOV lanes, so that the high infrastructure cost is not justified. Our paper aims to provide a rigorous analysis to study the effectiveness of introducing HOV lanes in terms of carpool intent and adoption. Previous studies do not have access to detailed carpool data (outside small-scale surveys). In this paper, however, we leverage a large granular data from Waze on carpool transactions both before and after introducing the HOV lanes.

Another stream of related research is the efficacy of incentives to boost carpooling. Vanoutrive et al. (2012) analyzed the popularity and determinants of carpooling in Belgium in the context of the workplace. The authors observed higher levels of carpooling at less accessible locations and in sectors such as construction, manufacturing, and transport. The recent work in Cohen et al. (2019) run a large field experiment to incentivize commuters to carpool. The authors found that financial incentives are not a successful driver for convincing commuters to carpool. On the other hand, targeting commuters who can save time by using an HOV lane is effective and can significantly increase carpool intent. While there is an extensive literature on incentives and motivations for carpooling, this paper aims to provide a comprehensive data-driven analysis on the impact of introducing HOV lanes on carpooling.

To conduct our analysis, we consider the introduction of the HOV lanes as a natural experiment. Studying the effect of a specific event (or intervention) is at the core of empirical research in social sciences (see, Dunning 2012, and the references therein). A natural experiment typically refers to the situation where the exposure to the experimental and control conditions was determined by nature as opposed to be manipulated by the researcher. Natural experiments can be useful when it

is clear which subpopulation was exposed (and which was not) and when the changes in outcomes may be attributed to the exposure. This type of empirical studies was extensively exploited in various contexts such as healthcare (Girotra et al. 2007, Craig et al. 2012, Staats et al. 2018), tax reforms (Cummins et al. 1994), mergers and acquisitions (Li and Netessine 2020), and filing an initial public offering (Cohen and Jiao 2018) just to name a few. In the context of ride-hailing, Zhang and Li (2017) examine periods both before and after the availability of Uber or Lyft in several locations and infer the effect on local consumer mobility and consumption patterns.

Structure of paper. In Section 3, we discuss the setting and data considered in this paper. Our results are presented in Section 4. Finally, we discuss the behavioral and policy implications of our findings in Section 5 and report our conclusions in Section 6.

3. Setting and Data

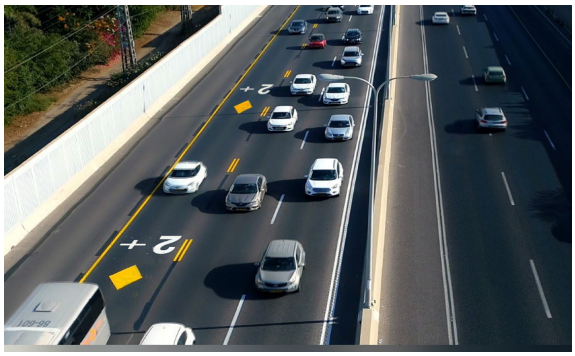
As discussed, we examine the impact of introducing the three Israeli HOV lanes in October 2019. Although these HOV lanes were strategically deployed in routes with a high level of traffic, the benefits of this policy has been the source of heated debates.

3.1. Setting

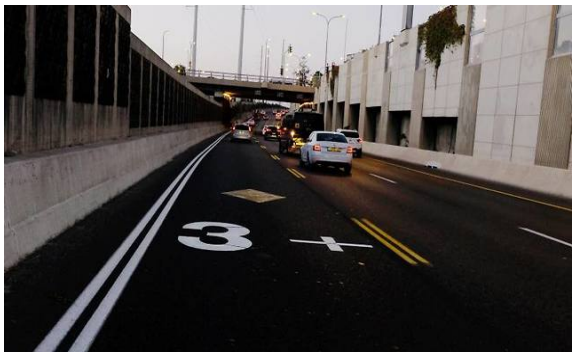
To guide our analyses, we have access to traffic and carpool data both before and after introducting the HOV lanes. Our data allows us to rigorously assess the impact of each HOV lane on commute time saving, and more importantly on carpool intent and adoption. We consider the three new Israeli HOV lanes introduced in October 2019:

1. **Netanya–Herzliya (HN):** This HOV lane connects the north part of the country (a city called Netanya) to the center of the country (Tel Aviv area) and aims to mainly affect morning commuters. This HOV lane is a 2+, that is, only vehicles with at least two occupants (one driver and one passenger) can use it. Before the introduction of the HOV lane, this highway used to have three regular lanes. After introducing the HOV lane, it moved to two regular lanes and one HOV lane (public transportation vehicles can also use the HOV lane) located on the right side.
2. **Herzliya–Netanya (NH):** This HOV lane covers the opposite direction than HN and aims to help evening commuters. This HOV lane is also a 2+ and has the same structure as HN.
3. **Mavo Ayalon–Kibbutz Galuyot (MK):** This HOV lane connects the southern part of the country (a city called Rishon LeTsiyon) to the center of the country. This HOV lane is a 3+, that is, only vehicles with a minimum of three occupants can use it. Before the introduction of the HOV lane, this highway used to have two regular lanes and one lane reserved for public transportation during morning hours (outside morning hours, any vehicle was allowed to use all three lanes). After introducing the HOV lane, it moved to two regular lanes and one HOV lane located on the left side.

It is important to highlight that these three HOV lanes were located along highly-used commute routes, potentially affecting tens of thousand commuters daily. An illustration can be seen in Figure 1. All three HOVs are free-of-charge for vehicles that satisfy the requirement. Vehicles that do not satisfy the requirement are not allowed to use the HOV lane (at any time of the day or night), and violators incur a monetary penalty, as we discuss next.



(a) HN HOV lane (source: Migdalor News, Jan. 2020)



(b) MK HOV lane (source: Ynet News, Jan. 2020)

Figure 1 Pictures of the Israeli HOV lanes.

3.2. Timeline

All three HOV lanes were introduced on the same day. In fact, the policy materialized in two phases: (1) a *soft enforcement* (on October 6, 2019) and (2) a *hard enforcement* (on November 3, 2019). During the soft enforcement period, drivers who violate the HOV lanes' requirement (e.g., solo car drivers) were given a warning without a monetary penalty. During the hard enforcement period, however, violators who are caught without enough passengers will have to pay a fine of 500 Shekels (approximately $144, as of January 2020).[6] The controls are managed by police patrols which can be parked in different parts of the HOV lanes. To examine the policy implication, we divide our data into three periods:

- **Before:** This is the period before the HOV lanes were introduced, spanning between September 1, 2019 and October 5, 2019.
- **Soft:** This is the period during the soft enforcement, spanning between October 6, 2019 and November 2, 2019.
- **Hard:** This is the period after the hard enforcement, spanning between November 3, 2019 and January 2, 2020.

[6] https://www.jpost.com/Israel-News/Drivers-violating-carpool-lane-laws-will-be-fined-606677

For each period, we removed the weekends (Friday and Saturday)[7] as well as the Jewish holidays. Indeed, during weekends and holidays, traffic is significantly reduced, so that these days become less relevant for the purpose of our analyses. Note that extensive media coverage (TV, radio, Internet news) on these HOV lanes was deployed to ensure a high level of awareness. As we can see from Figure 2, the Google Trends data in Israel on four queries related to the HOV lanes policy (called "Nativ Plus" in Hebrew) has started to take off before the hard enforcement period. Interestingly, as soon as people started talking about "Nativ Plus" (which is a new term introduced in the context of the HOV lanes), we can observe a spike in the number of queries for "Carpool."

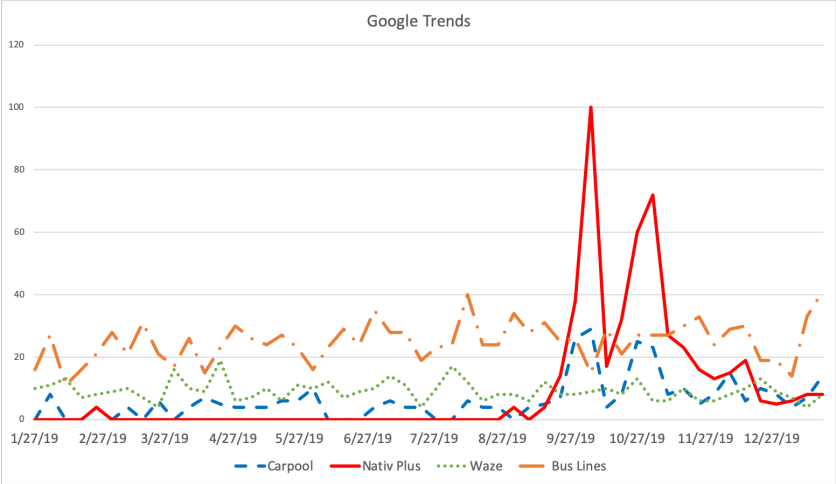


Figure 2 Google Trends results in Israel for four search queries related to the HOV lanes policy—in Hebrew: Carpool, "Nativ Plus," Waze, and Bus Lines (Source: Google Trends, Jan. 2020).

3.3. Key Metrics

The main goals of introducing an HOV lane is to incentivize commuters to carpool and save time on their daily commute. As a result, we consider metrics that capture these goals. We first consider the time saving (computed as the difference between the time it takes to complete a navigation with and without using the HOV lane). This metric is closely related to the effectiveness of the HOV lanes in terms of reducing commute time.

In addition to the Waze data on time saving, we also have access to carpool data. As discussed before, Waze launched a platform to help users find carpool matches. The carpool service was introduced to Israel in 2015 and is now offered in the U.S., Brazil, Mexico, and Israel. As of September 2019, 550,000 carpool rides were completed globally and the company expects to cross 1 million monthly rides by early 2020.[8]

[7] Note that in Israel, the work days are Sunday to Thursday.

[8] https://www.theverge.com/2019/10/10/20906281/waze-carpool-anniversary-stats-update-fee-navigation-drivers

To capture the different steps in the "carpool funnel," we consider the following three variables: number of offers sent by drivers, number of offers sent by riders, and completed carpools. Note that all these carpool variables are standardized and defined over routes starting in a specific cell and ending in another cell (see more details in Section 3.4). The beginning of the funnel corresponds to the carpool intent (i.e., sending an offer through the Waze platform), whereas the end of the funnel measures the actual action of completing a carpool ride. Our dependent variables are summarized in Table 1.

Table 1 Dependent variables (all carpool variables are standardized over a Xkm square cell)

Variable	Description
Time saving	Time difference between using versus not using the HOV lane
Number of offers sent by drivers	Number of offers sent by drivers via the carpool platform
Number of offers sent by riders	Number of offers sent by riders via the carpool platform
Completed carpools	Number of completed rides via the carpool platform

We will compare the above variables during each of the three periods (before, soft, and hard) by computing the daily averages. We will naturally separate morning commutes (i.e., from 6AM to 11AM) and evening commutes (i.e., from 3PM to 8PM). In order to isolate the impact of the HOV lanes, we need to carefully select the commute routes which are the most concerned by the introduction of the HOV lanes, as discussed next.

3.4. Routes Selection

For each of the three HOV lanes, we carefully select the most relevant commute routes. A critical part of our design relates to how we should select the routes that should be affected by the introduction of the HOV lanes. Our process goes as follows:

1. We divide the entire country of Israel in "cells." Each cell is a X-by-X square kilometer (due to confidentiality, we cannot reveal the value of X). A navigation request (through the Waze navigation app) originating from one cell and ending in another cell is called a route.[9]
2. Each of the three HOV lanes is divided into disjoint segments. Each segment is approximately one kilometer long, so that concatenating all the segments yields the entire HOV lane.
3. For each HOV lane, we consider all the routes (from one cell to another) that overlap with at least 50% of the HOV segments.
4. We then retain the seven most popular routes in terms of number of navigation requests during the 40 days prior to the introduction of the HOV lanes.

[9] If the same user requests several navigations successively, we count those as a single navigation request. In other words, we focus on navigation requests originating from distinct users.

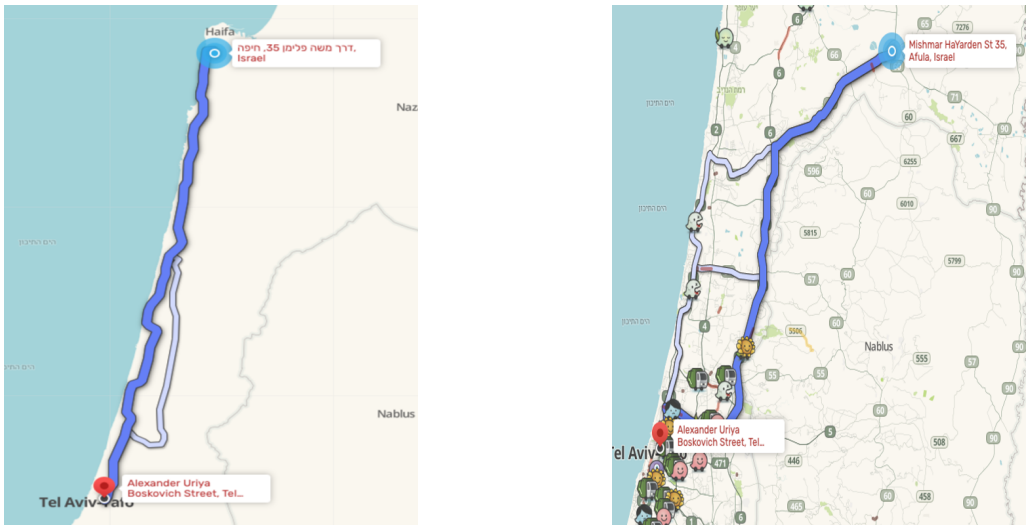
The above process naturally yields routes which are (i) supposed to be directly affected by the introduction of the HOV lanes (i.e., a high overlap with the HOV segments) and (ii) are popular among commuters (i.e., a large number of navigation requests). In addition, we impose a minimum of 10 minute duration and we carefully double check that each selected route is indeed relevant to our context. At the end of this process, we obtain 21 routes, which we call the *treated routes*.

To create a benchmark for our analyses, we also select control routes. Defining appropriate control routes helps us control for seasonality effects and account for external variation (e.g., national advertisement campaigns). Specifically, we consider two types of control routes:

1. **Control 1:** For each treated route, we seek to find a similar route with the same destination (and a different origin) that is not supposed to be affected by the HOV lanes. Specifically, for each treated route, we identify all the routes with the same destination and record the distance (in kilometers) and number of navigation requests (from unique users) during the past 40 days. We then find the route that is the closest to the treated route in terms of distance and number of navigation requests. Finally, we ensure that the route (i) does not have a significant overlap with the HOV lanes (less than 5% of the segments) and (ii) is not extremely similar to the treated route (e.g., two neighboring origin cells).
2. **Control 2:** For each treated route, we seek to find a similar route—with a different destination and a different origin—that is not supposed to be affected by the HOV lanes. Specifically, for each treated route, we identify all the routes across the entire country and record the distance and number of navigation requests during the past 40 days. We then find the route that is the closest to the treated route in terms of distance and number of navigation requests. As before, we ensure that the route does not have a significant overlap with the HOV lanes.

We use routes with the same destination as the treated routes to capture the same level of local awareness. The routes from Control 2 correspond to a more generic control condition that captures the general awareness across the entire country. An example of a treated route and the corresponding route from Control 1 are presented in Figure 3. Both routes have the same destination (in this case a specific cell in Tel Aviv) but different origins. The treated route goes through the NH HOV lane, whereas the Control 1 route does not.

When selecting the control routes, it is possible that we could not find a good match for certain treated routes. If none of the routes have a distance and a number of navigation requests within 40% of the treated route, we do not select a control route. In our process, this happened four times (two Control 1 routes are missing for HN, one Control 2 route is missing for NH, and one Control 2 route is missing for MK). As a result, we have a total of 38 control routes. Note that the process of identifying control routes does not use any of the carpool data. This aims to ensure that the design of our study is not biased toward carpooling behavior, which is the main purpose of our analysis.



(a) Treated route (from a cell in Haifa to a cell in Tel Aviv)

(b) Control 1 route (from a cell in Afula to a cell in Tel Aviv)

Figure 3 **Example of a treated route and the corresponding route from Control 1 for the NH HOV lane.**

Our study focuses on our 21 treated routes (seven for each HOV lane) and our 38 control routes (approximately two control routes for each treated route). We report the relevant summary statistics on these 59 routes in the next section. For robustness purposes, we also consider the problem where the data is aggregated at the city level, that is, instead of defining cell-to-cell routes, we define city-to-city routes (see Section 4.4 for more details).

3.5. Data

To examine the impact of the HOV lanes, we use traffic and carpool data from Waze. In Tables 2–4, we present the summary statistics on our 59 routes aggregated across all three HOV lanes for each of the three periods (before, soft, and hard).

Table 2 **Summary statistics aggregated across all three HOV lanes in the before period over a Xkm square cell**

Variable – Mean (standard deviation)	Treated	Control 1	Control 2
Number of offers sent by drivers	60.7 (6.93)	62.95 (9.24)	51.85 (9.64)
Number of offers sent by riders	81.98 (16.54)	94.45 (20.7)	74.94 (19.1)
Completed carpools	6.45 (0.8)	6.69 (1.1)	7.09 (1.31)
Number of navigations (normalized)	100%	98.78%	88.61%
Ride value (local currency—Shekels)	9.12 (2.15)	8.28 (1.14)	9.04 (1.96)

In Tables 2–4, the variables are averaged over the total number of routes and number of days. Since each route is defined at the cell-to-cell level (starting in a Xkm square cell and ending in another cell), each value represents the average over a Xkm square cell. In addition to the three carpool variables (offers sent by drivers, offers sent by riders, and completed carpools), we report the number of navigation requests (from Waze) and the ride value (price paid to the driver for

Table 3 **Summary statistics aggregated across all three HOV lanes in the soft period over a Xkm square cell**

Variable – Mean (standard deviation)	Treated	Control 1	Control 2
Number of offers sent by drivers	215.75 (18.2)	105 (8.09)	114.25 (11.65)
Number of offers sent by riders	193.5 (12.52)	243.75 (40.56)	205.5 (27.81)
Completed carpools	16.75 (1.2)	18.25 (2.16)	22.5 (1.99)
Number of navigations (normalized)	112.53%	111.51%	95%
Ride value (local currency—Shekels)	9.74 (3.01)	8.29 (1.02)	9.4 (2.37)

Table 4 **Summary statistics aggregated across all three HOV lanes in the hard period over a Xkm square cell**

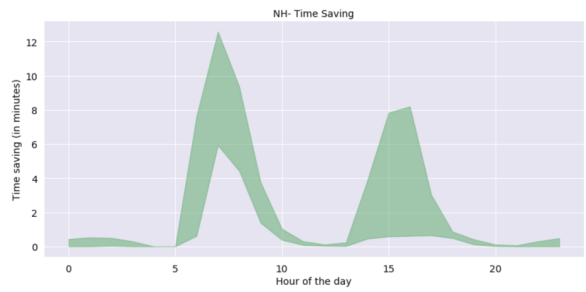
Variable – Mean (standard deviation)	Treated	Control 1	Control 2
Number of offers sent by drivers	390.5 (22.23)	202.83 (16.29)	178.46 (17.32)
Number of offers sent by riders	286.54 (20.69)	239.25 (27.52)	222.71 (24.55)
Completed carpools	22.96 (1.36)	22.92 (2.42)	26.06 (2.67)
Number of navigations (normalized)	122.4%	125.42%	106.28%
Ride value (local currency—Shekels)	8.76 (2.26)	8.32 (1.59)	9.16 (2.4)

the ride excluding bonuses and referrals). We normalize the number of navigation requests so that the routes in Control 1 are assigned a value of 100%. One can see that the average number of navigations is similar across all three types of routes. We also observe that all the carpool metrics increase substantially after the introduction of the HOV lanes. This shows that the impact of the policy goes beyond the treated routes and can also affect the routes which are not directly affected by the HOV lanes (we will carefully revisit this finding in Section 4). Since the effect may be different for each HOV lane and time of the day, we will conduct a separate analysis for each HOV lane and time period (morning or evening).

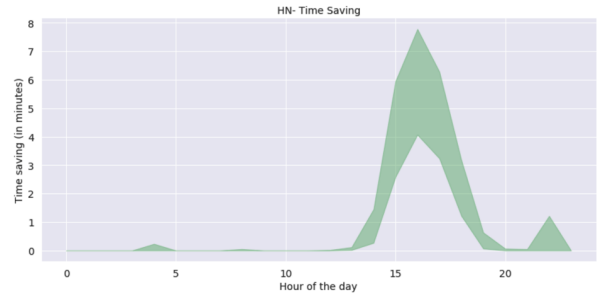
3.6. Time Saving

Before presenting our results on the carpool variables, we compute and plot the time saving for each HOV lane (see Figure 4) by considering all the navigations (using Waze) across the 21 treated routes defined in Section 3.4. We focus on the period after the introduction of the HOV lanes (i.e., by aggregating the soft and hard periods) and compute the difference between the estimated time it takes (in minutes) to complete the navigation with and without using the HOV lane. Note that the time saving before the introduction of the HOV lanes is zero by definition (similarly, the time saving for the control routes is not relevant). The estimated times (with and without the HOV lane) are calculated in real-time for each navigation request using Waze data and algorithms. In Figure 4, we aggregate the observations using a 10-minute time window and plot the 40-th and 60th percentiles as a function of the time of the day.

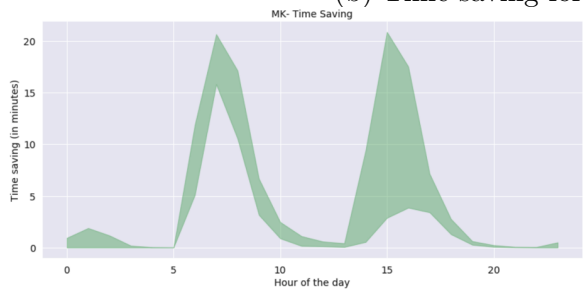
As we can see, commuters can expect to gain a significant commute time by using the HOV lanes, especially during rush hours. This is reassuring given that this was the original goal of the policy. As mentioned before, NH and MK are mostly beneficial during morning hours, whereas HN is more beneficial during evening hours. The maximum median time savings are 8.1, 5.7, and 15.7 minutes for NH, HN, and MK respectively.



(a) Time saving for NH



(b) Time saving for HN



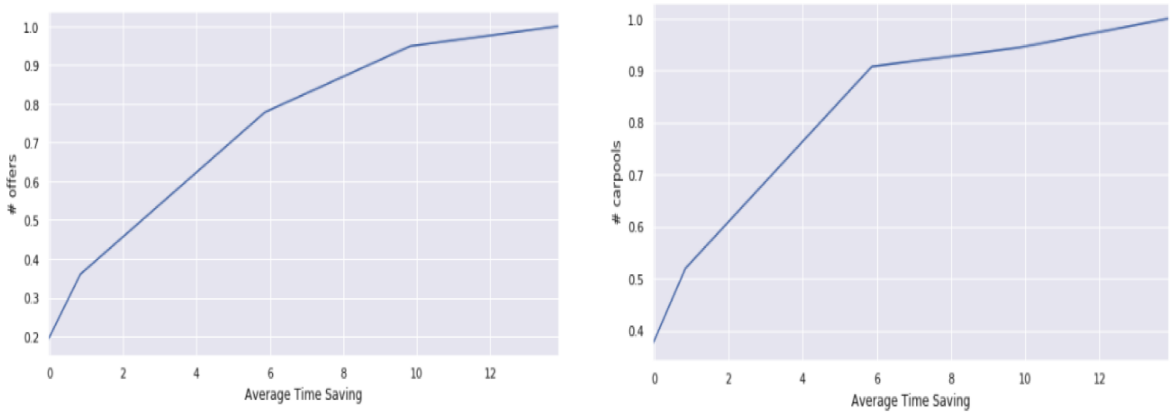
(c) Time saving for MK

Figure 4 Distribution of the time saving across the day for the three HOV lanes.

Our data suggests that the introduction of the HOV lanes led to a significant time saving—between 20% and 50% of the total commute time—for commuters who satisfy the requirement. In the same vein, it is natural to believe that commuters who cannot use the HOV lanes experience some frustration and are potentially interested in carpooling. Indeed, saving 15 minutes on each commute direction every workday would amount to saving five full days annually. In traditional settings, measuring the carpool rate can be hard, if not impossible. Having access to the carpool Waze data provides us with a unique opportunity to examine whether the introduction of the HOV lanes had an actual impact on carpooling. Still, it is worth mentioning that our carpool data is limited and has restrictions. First, we only have access to a portion of the carpools and may miss a large number of carpool transactions. Second, our data may suffer from biases (e.g., the carpool platform may be primarily used by early adopters or some specific types of users). That said, these restrictions are mitigated by the fact that we benchmark our results relative to the control routes. In addition, the Waze carpool platform is definitely considered as a popular means of finding carpool rides in Israel. Since a large portion of Israeli car commuters use Waze as a navigation app, Waze has promoted the carpool platform directly into the navigation app. This product feature along with substantial marketing efforts have increased the awareness of Israeli commuters about the Waze carpool platform.

Using data from U.S. commuters, Cohen et al. (2019) show that the time saving by using the HOV lane has a positive correlation with the carpool intent. In Figure 5, we use the Israeli carpool data on the 21 treated routes and plot the number of offers sent by drivers and the number of

completed carpools as a function of the time saving. In this figure, we normalize the numbers by applying a conversion factor so that the highest number is assigned the value of 1.0 and all other values are adjusted by the same normalizing factor—maintaining the same relationship between different points. As in the U.S. data, we can see a positive correlation between the time saving using the HOV lane and both the carpool intent (i.e., sent offers) and carpool adoption (i.e., completed carpools). To test the robustness of this finding, we estimated several regression specifications by considering both dependent variables (offers sent by drivers and number of carpools), adding HOV lanes fixed effects, and controlling for several factors such as the distance with and without using the HOV lane, the period (before, soft, hard), and the number of navigation requests (the regression estimates are reported in Table 7 in the Appendix).



(a) Offers sent by drivers (b) Completed carpools

Figure 5 Positive correlation between the time saving from the HOV lane and carpool intent and adoption.

4. Results

We first present an aggregated analysis on the impact of introducing the three HOV lanes on the entire country. We then focus on the 59 routes (21 treated routes and 38 control routes) discussed in Section 3.4 and present the results based on statistical tests. We also conduct several robustness tests such as modifying the regression specification and considering a dataset built at the city level (i.e., instead of looking at Xkm square cells, we aggregate the data at the city-to-city level).

4.1. Country-Level Analysis

Before presenting the results at the route level, we first investigate the growth rate for the entire country during the period of interest. In a way, this is the simplest way to examine the overall impact of introducing the HOV lanes without any assumptions or any route selection. In Figure 6, we plot the growth rate between mid August 2019 and mid January 2020 for the entire country of Israel (all the numbers are relative to the first point in the graph, i.e., 2019-08-18). Since we removed

the weekends, each week corresponds to a five-day period. As opposed to focus only on the treated and control routes, we consider all the carpool rides across the entire country and split them into two categories: the rides that overlap with one of the three HOV lanes (labeled as "HOV routes") and the other rides (labeled as "Non-HOV routes"). As we can see, before the introduction of the HOV lanes, the growth rate is similar for both types of routes (in fact, the growth rate for non-HOV routes is slightly higher). Right after the introduction of the HOV lanes (hard enforcement period), we observe a striking gap between the two types of routes. Specifically, between November 1, 2019 and December 1 2019 (i.e., during the first month following the hard enforcement), the slope of the growth for HOV routes becomes much steeper than the slope for non-HOV routes. In the same spirit, in Table 5, we compute the average week-over-week growth (in this case, we compute the growth rate relative to the previous week) before and after the introduction of the HOV lanes, for both HOV and non-HOV routes. Right after the beginning of the hard enforcement period, we find a relative increase of 76.5% [=(10.38-5.88)/5.88] for HOV routes relative to non-HOV routes. For the longer term (i.e,. between December 1 2019 and January 12, 2020), the relative increase is 61.1%. For the HOV routes, we can attribute this significant growth increase to the introduction of the HOV lanes (in addition to the usual organic growth). For the non-HOV routes, we believe that the boost in growth comes mainly from an increased public awareness about carpooling induced by the media buzz related to the HOV lanes.

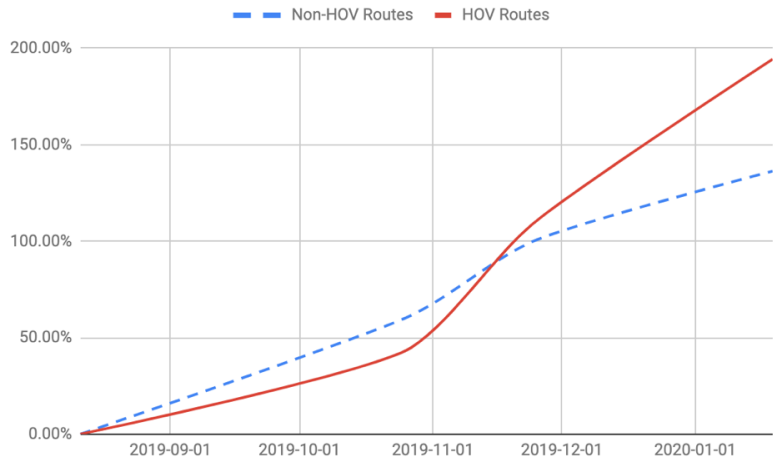


Figure 6 **Weekly growth rate for carpool rides in Israel during the period of interest.**

Table 5 **Week-over-week growth before and after the introduction of the HOV lanes**

	Before	Right After	After (longer-term)
Non-HOV routes	2.68%	5.88%	3.55%
HOV routes	1.95%	10.38%	5.72%

As discussed, the growth has increased not only in the HOV routes but also in the non-HOV routes. Several reasons can explain this increase. First, the Waze carpool platform is still definitely in a growth phase so that the increase can be attributed to a positive trend. Second, the media buzz that revolved around the new HOV lanes has increased awareness to the public about the opportunity of carpooling. To analyze the impact of introducing the HOV lanes, the first question we want to address is whether the growth is higher for HOV routes relative to non-HOV routes. Figure 6 and Table 5 suggest that this is indeed the case.

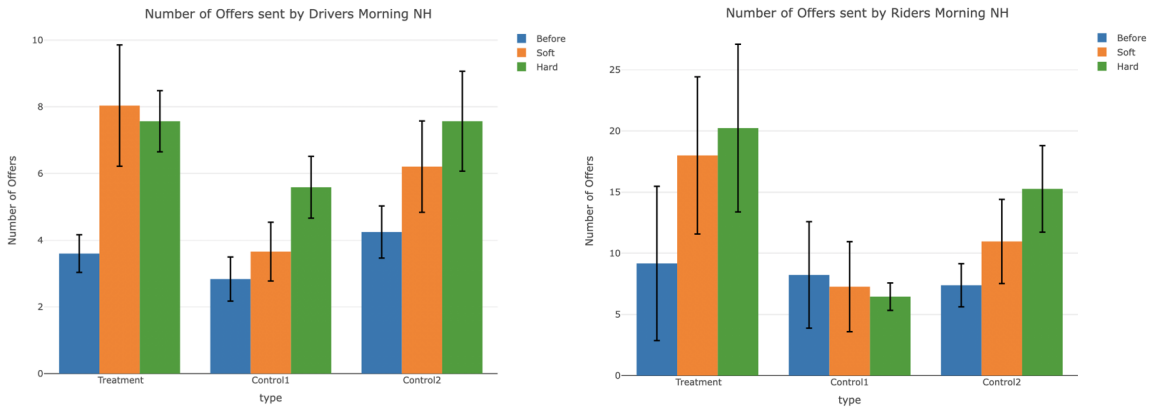
4.2. Route-Level Analysis

We next focus on the 21 treated routes which are affected by the introduction of the three HOV lanes. We also consider our 38 control routes as a benchmark. We then compare the average of our dependent variables in the three different periods. We next present the results for each HOV lane.

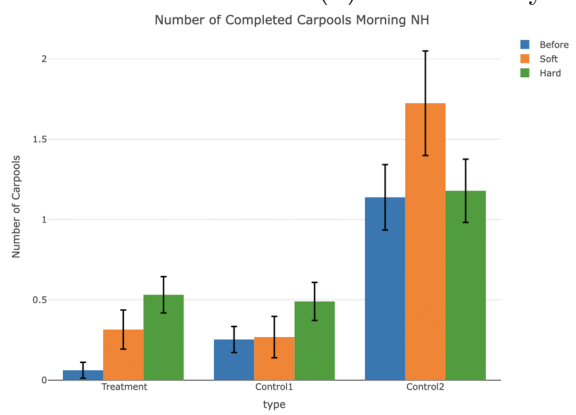
4.2.1. Netanya–Herzliya (NH): For NH, the impact is expected to mainly occur during morning hours. In Figure 7, we focus on the seven routes related to NH. We compare the number of offers sent by drivers and by riders as well the number of completed carpools across the three periods (before, soft, and hard). Since each route is defined at the cell level (starting in a Xkm square cell and ending in another cell), each variable represents the average over a Xkm square cell. We observe that both metrics increase significantly for the treated routes after introducting the HOV lane. Specifically, the number of sent offers increases by 100%, and the number of completed carpools raises by more than 900% for the treated routes. As mentioned, these metrics also increase for the two types of control routes. Such an increase can be potentially attributed to seasonality trends or an increased level of public awareness about carpooling. As one can see in Figure 7, the increase is much higher in relative terms (with respect to the period before the policy change) for the treated routes.

Furthermore, we find that the number of offers sent by riders does not significantly increase. This finding is inline with our expectations, since the policy change (i.e., introducing an HOV lane) was targeted to drivers and did not aim to directly target riders (e.g., commuters who do not own a car). Finally, all our focal metrics are not affected (in a statistically significant way) when we run the same analysis during the evening hours.

4.2.2. Herzliya–Netanya (HN): For HN, the impact is expected to occur during evening hours. In Figure 8, we focus on the routes related to the HN. We compare the number of offers sent by drivers and by riders as well as the number of completed carpools across the three periods. As before, we observe that both metrics increase significantly for the treated routes after introducing the HOV. Specifically, the number of sent offers increases by 200%, and the number of completed carpools raises by 100% for the treated routes. These metrics also increase for the second type of



(a) Offers sent by drivers (b) Offers sent by riders



(c) Completed carpools

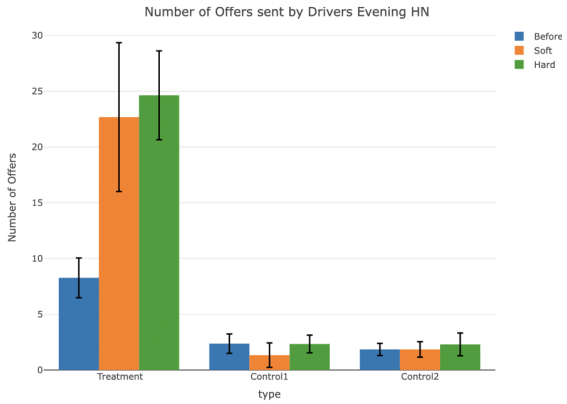
Figure 7 Comparing the offers sent by drivers, riders, and the completed carpools for NH during morning hours (averaged over a Xkm square cell).

control routes. However, once again, the increase is much higher in relative terms (with respect to the period before the policy change) for the treated routes. Interestingly, we find that the impact for HN routes is lower relative to NH. This is not surprising since it is typically harder to find a carpool ride back from work to home (probably because schedules are less predictable and flexible during evening hours).

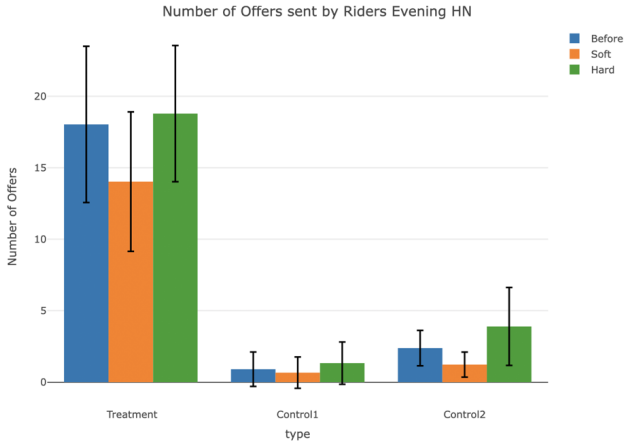
We also find that the number of offers sent by riders does not significantly increase and that all the metrics are not affected (in a statistically significant way) when we run the same analysis during the morning hours.

At this point, our analyses suggest that both NH and HN had a strong impact on drivers' carpool intent (captured by sent offers) and on carpool actions (captured by the number of completed carpool via the Waze platform). As expected, each HOV lane has an impact during the hours where it is the most useful. Thus, our findings validate the fact that the policy was effective for these two HOV lanes.

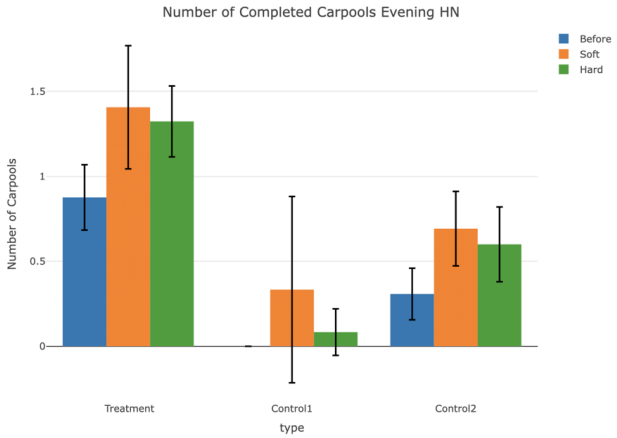
4.2.3. Mavo Ayalon–Kibbutz Galuyot (MK): For MK, the impact is expected to occur during morning hours. In Figure 9, we focus on the routes related to MK. We compare the number



(a) Offers sent by drivers



(b) Offers sent by riders



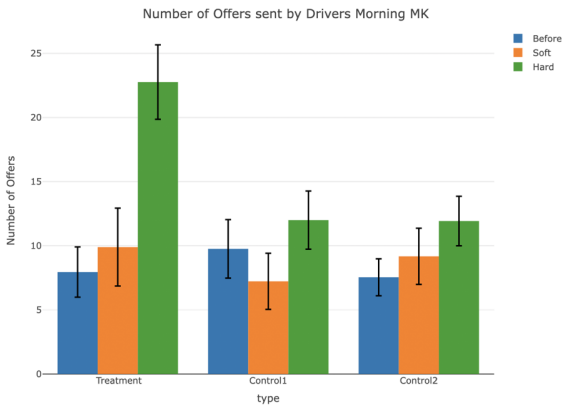
(c) Completed carpools

Figure 8 Comparing the offers sent by drivers, riders, and the completed carpools for HN during evening hours (averaged over a Xkm square cell).

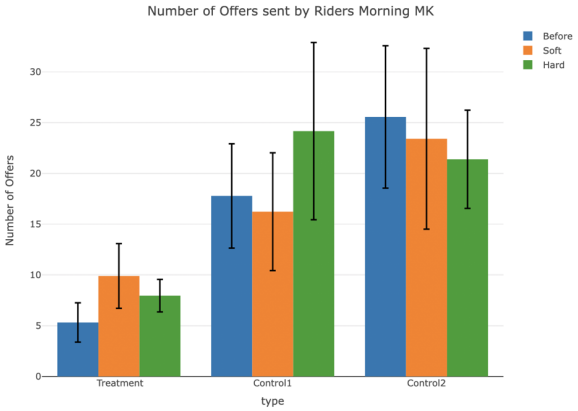
of offers sent by drivers and by riders as well as the number of completed carpools across the three periods. In this case, we find that the number of sent offers increases by 200% after the hard enforcement period for the treated routes (it does not significantly increase during the soft enforcement). We also find that the number of completed carpools is not significantly affected. This result bears an interesting potential insight. Recall that this HOV lane requires at least three occupants in the vehicle. Given the high potential time saving, several drivers are actively trying to find riders (by sending more offers through the Waze carpool platform). It seems that finding two riders is not easy, so that many drivers are often not successful. Consequently, these drivers are more likely to cancel the ride, so that the number of completed carpools is not affected. This evidence is supported by Figure 10 which shows that the number of cancellations is indeed higher during the hard period for the treated routes. Importantly, the difference in the number of cancelations before the policy and after the hard enforcement is not statistically significant for the two other HOV lanes (NH and HN). This shows that the market dynamics plays an important role

to translate an increased number of sent offers to an actual higher number of completed carpools. The routes overlapping with MK do not seem to have enough riders interested in carpooling, so that an increased intent on the drivers' side have no impact on carpool adoption. Thus, our analysis suggests that introducing a 3+ HOV lane is less impactful relative to a 2+ HOV in terms of completed carpools. While the carpool intent did increase, we do not observe a statistically significant effect on the completed carpools. This is especially interesting given that the median time saving for MK was the highest (see Section 3.6).

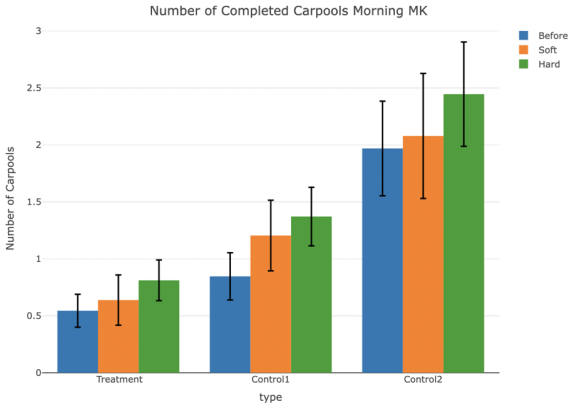
As before, we find that the number of offers sent by riders does not significantly increase and that all the metrics are not affected (in a statistically significant way) when we run the same analysis during the evening hours.



(a) Offers sent by drivers



(b) Offers sent by riders



(c) Completed carpools

Figure 9 Comparing the offers sent by drivers, riders, and the completed carpools for MK during morning hours (averaged over a Xkm square cell).

For robustness purposes, we repeat the above analyses using bootstrapping. Specifically, for each HOV lane, we randomly sample routes (with replacement) across 100 independent iterations. We obtain the same qualitative results and insights, hence confirming the robustness of our results. In addition, we estimate several regression specifications, as discussed next.

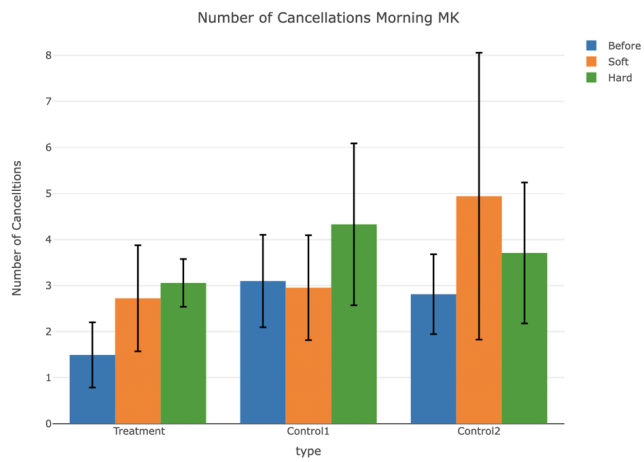


Figure 10 **Total number of canceled rides for MK during the morning hours (averaged over a Xkm square cell).**

4.3. Regressions

We next test the robustness of the previous results by estimating a regression model, allowing us to control for various factors. Our specification is a log-transformed ordinary least square model:

$$\log(Y_t^k + 1) = \alpha \text{period\_type} + \beta \text{route\_type} + \gamma \text{period\_type} \times \text{route\_type} + \epsilon_t^k, \tag{1}$$

where each observation is at the day-route (t, k) level. Y_t^k is one of our carpool dependent variables (see Table 1) such as the number of sent offers by drivers during day t on route k. We then include three independent variables: (1) period_type, which determines the period (before, soft, hard) of observation (t, k), (2) route_type which captures the route type (treated, Control 1, Control 2), and (3) the interaction between these two variables. Finally, ϵ_i^k is a stochastic i.i.d Gaussian term. We are especially interested in the effect of the interaction coefficient γ between the treated routes and the hard period. We set the baseline of this regression as the period before introducing the HOV lanes and for the routes in Control 2.

To showcase the robustness of our results, we estimate the specification in Equation (1) under various configurations. We first estimate a separate regression for each HOV lane. We then consider the pooled sample while controlling for the specific HOV lane. We next add additional controls such as the day of the week, the time of the day, the number of navigation requests for this route, and the distance (in kilometers) of the carpool ride. Finally, we also estimate an aggregate model where all the seven routes for each HOV lanes are aggregated. Due to space limitations, we only report the regression results for the pooled sample. The estimates of the interaction coefficient γ between the treatment condition and the hard period are presented in Table 6 (the complete regression tables can be found in Tables 8–10 in the Appendix). As we can see from Table 6, the number of offers sent by drivers are higher for the treated routes across all three HOV lanes. However, the number of completed carpool increases significantly only for NH (it is close to be statistically significant for HN and far from it for MK). It thus confirms our findings from Section 4.2.

Table 6 Regression estimates of the interaction coefficient γ between treatment and the hard period

	Offers Sent by Drivers	Offers Sent by Riders	Completed Carpools
NH Morning	0.3098***	0.3050**	0.2776***
	(0.091)	(0.121)	(0.037)
HN Evening	1.2406***	0.3771*	0.1064
	(0.163)	(0.207)	(0.076)
MK Morning	0.8764***	0.0632	-0.0613
	(0.103)	(0.123)	(0.049)

4.4. City-Level Analysis

Instead of focusing on routes defined at the cell level (i.e., navigation requests from one Xkm square cell to another), one can instead conduct an analysis at the city level. Specifically, we now define a route to be between a pick-up city and a drop-off city (e.g., Haifa to Tel Aviv). We focus on the most popular routes by restricting the daily number of navigation requests (using Waze) to be at least 600. This restriction led us to the 35 most popular city-to-city routes in the entire country. We then use the data from the period after the introduction of the HOV lanes to compute the average time saving (by using the HOV lane) for each of the 35 routes. For 12 out of 35 routes, we find a time saving higher than 3 minutes. We then assign these 12 routes to the treatment condition and the remaining 23 routes to the control condition. Using the routes defined at the city level, we repeat the same analysis as before (while bootstrapping over 100 iterations) and find that most of our qualitative results and insights still hold (the details are not reported to avoid repetitions).

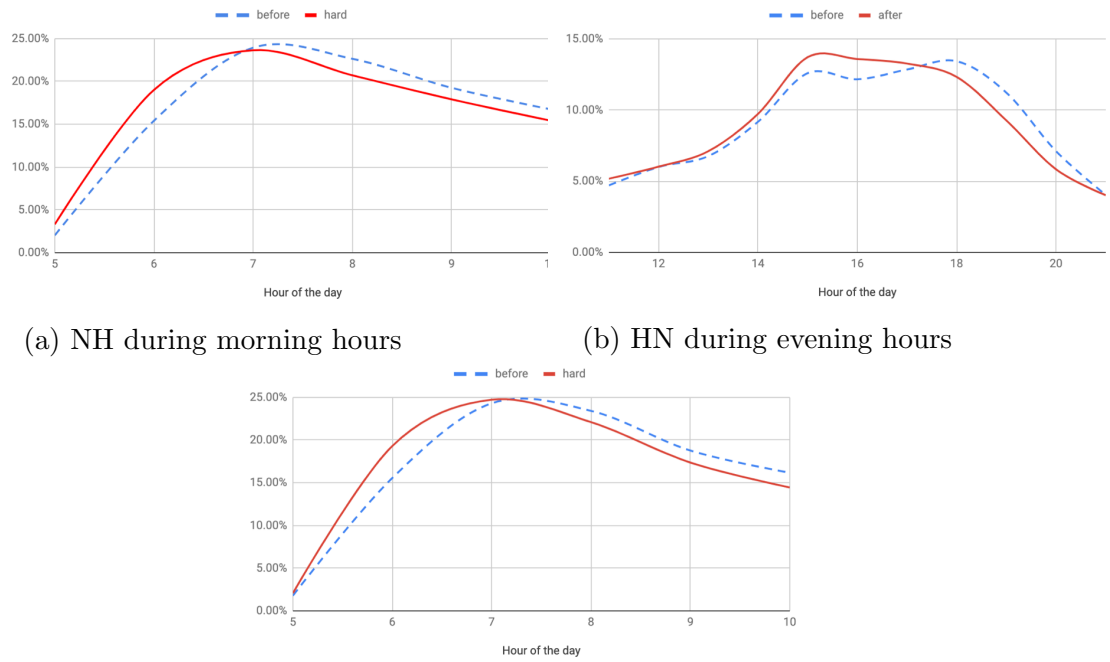
5. Behavioral and Policy Implications

In this section, we present the implications of our results. First, we examine whether the introduction of the HOV lanes has triggered a strategic commuting behavior. Specifically, we investigate whether commuters have strategically adapted their commute time (e.g., by leaving earlier than before) in anticipation of a higher level of traffic. Second, we report the policy implications from our study including potential recommendations for planning HOV lanes' requirements.

5.1. Strategic Commuting Behavior

While it is clear that the introduction of an HOV lane has a spatial spillover effect (i.e., commuters are more likely to use alternative routes), an equally interesting question is whether it has a spillover effect in time. In other words, instead of carpooling, maybe certain commuters are strategically changing their commute time in response to the introduction of the HOV lane. To study this question, we consider each HOV lane and plot the percentage of Waze navigation requests (not necessarily carpool rides) during each time of the day. The data is aggregated using a 10-minute window, and we separate the period before and after the introduction of the HOV lane (for this analysis, we focus on the hard period). The results for NH, HN, and MK are presented in Figure 11. We can see that—consistently for all three HOV lanes—commuters tend to shift their commute

time backward in time. They seem to anticipate the fact that their commute will take longer and respond by leaving at an earlier time. For the NH HOV lane, 17.43% of the commuters leave between 5AM and 7AM (i.e., before the rush hour period) before introducing the HOV lane, versus 22.33% in the hard period. This corresponds to a relative increase of 28%. For comparison, these numbers become 16.32% and 18.93% for the routes in the Control 2 group (i.e., a relative increase of 16%). Similarly, for the MK HOV lane, 17.34% of the commuters leave between 5AM and 7AM before introducing the HOV lane, versus 21.38% in the hard period. This corresponds to a relative increase of 23.3% compared to 9.29% for the routes in the Control 2 group. For both HOV lanes, we observe a clear trend of commuters leaving at earlier times. A similar trend is also observed for HN, albeit with a smaller magnitude. This may be explained from the fact that HN is mainly used during evening hours, so that many commuters cannot easily leave work on the earlier side.



(a) NH during morning hours (b) HN during evening hours

(c) MK during morning hours

Figure 11 Distribution of the time spillover effect for the three HOV lanes.

We conclude that the introduction of HOV lanes does not only incentivize more commuters to carpool, it can also induce commuters to switch their behavior by shifting their commute time earlier. This finding can be viewed as a great impact given that most traffic congestion problems occur during specific rush hours.

5.2. Policy Implications

Our analyses provides evidence that introducing HOV lanes can increase the number of carpools. Interestingly, the routes which are not affected by the HOV lanes also experienced an increase in

the number of carpools. This increase can be partially attributed to the growth of the carpool platform but also to the increased level of public awareness about carpooling. Our study also shows that the market dynamics plays an important role when deciding the requirements for using the HOV lane. Given that the introduction of an HOV lane directly incentivizes only one side of the market (drivers), it can be effective to combine this policy with riders' incentives. In addition, before deciding between a 2+ and a 3+ requirement, it can be helpful to conduct some market research to understand the asymmetry between demand and supply. Since most of the traffic occurs during a specific time window, it can also be beneficial to dynamically vary the HOV requirements throughout the day, as done in several cases. More importantly, our analyses and results show that the impact of an HOV lane can go beyond incentivizing commuters to carpool and use the HOV lane. First, we found an awareness effect so that the carpool intent and adoption are likely to increase also for routes that do not overlap with the HOV lane. Second, commuters may decide to strategically adapt their commute time and hence reduce the traffic congestion during peak hours. Finally, we observed that the impact for the routes that are used for evening commutes (i.e., from work back to home) is less substantial relative to routes used for morning commute (i.e., from home to work). A suggested policy implication would be to offer a ride back to riders who are interested in carpooling. This will remove the uncertainty and can positively impact consumer behavior.

We live in a society where the potential for carpooling is unprecedented. The access to real-time data and efficient matching platforms can allow commuters to find great matches for carpooling. According to Waze data, close to two thirds of drivers have at least one other regular Waze driver with a "perfectly matching commute", that is, driving from the same origin to the same destination, within less than 500 meters radium from each. This translates to tens of thousands of daily commuters who have a neighbor (whom they do not know) with a similar commute (locations and times). Deploying HOV lanes in strategic places coupled with enhanced technology that can help commuters to find those perfect matches has the potential to massively increase carpool adoption and commuters' happiness.

6. Conclusions

This paper conducts a data-driven investigation on the impact of introducing three HOV lanes in Israel on carpooling. We have access to a granular dataset on traffic and carpool transactions from Waze both before and after introducing the HOV lanes. This allows us to examine the impact of the HOV lanes on carpool intent and adoption. To guide our analysis, we first carefully select routes which are supposed to be affected by the HOV lanes (treated routes). We then select similar routes which are not supposed to be affected by the HOV lanes (control routes).

Our first result validates the fact that the treatment took place, that is, commuters are using the HOV lane and can save a median commute time during rush hours of 5.7–15.7 minutes. We

then compare the different carpool variables, from carpool intent to carpool adoption. For the two HOV lanes with a 2+ restriction, we find that both the number of sent offers by drivers and the number of completed carpools significantly increase. At the same time, the number of offers sent by riders is not significantly affected. This is inline with the fact that the policy is directly targeted to drivers. For the third HOV lane—which requires at least three vehicle occupants—we find that only the number of sent offers by drivers increases. The introduction of the HOV lane stimulates the drivers' carpool intent who are trying to find riders. Since finding two riders is not easy, several drivers cancel their ride request and end up not carpooling. This shows that the market dynamics and the balancedness of both market sides (drivers and riders) should be taken into account when determining the HOV lane's requirement. Our results suggest that a 2+ requirement was more successful than a 3+ requirement in terms of completed carpools. Interestingly, we find that the new HOV lanes have a global impact as they also raised the carpool rates for routes unaffected by the HOV lanes. This boost can be explained by the increased awareness of the public about the opportunity of carpooling. Finally, we observe that commuters are able to anticipate the traffic increase and adapt their commute times. Such time spillover effects can play a critical role in alleviating traffic congestion.

Several caveats are in order. First, our carpool data is only a partial representation of the entire picture. Several commuters are likely to carpool without using the Waze platform. As a result, we cannot quantify the overall impact on carpooling. Second, our analysis focuses on the short-term impact, but it is also important to consider a more long-term impact. Third, we do not have access to public-transportation data which is an additional relevant matter, left for future research.

Acknowledgments

We would like to thank Yotam Givati for excellent research assistance on the data collection process and on running some of the basic analyses.

References

Boriboonsomsin K, Barth M (2007) Evaluating air quality benefits of freeway high-occupancy vehicle lanes in southern california. *Transportation research record* 2011(1):137–147.

Cohen M, Fiszer MD, Ratzon A, Sasson R (2019) Incentivizing commuters to carpool: A large field experiment with waze, available at SSRN 3458330.

Cohen M, Jiao K (2018) The impact of ipos on peer-to-peer lending platforms, available at SSRN 3292987.

Craig P, Cooper C, Gunnell D, Haw S, Lawson K, Macintyre S, Ogilvie D, Petticrew M, Reeves B, Sutton M, et al. (2012) Using natural experiments to evaluate population health interventions: new medical research council guidance. *J Epidemiol Community Health* 66(12):1182–1186.

Cummins JG, Hassett KA, Hubbard RG, Hall RE, Caballero RJ (1994) A reconsideration of investment behavior using tax reforms as natural experiments. *Brookings papers on economic activity* 1994(2):1–74.

Dahlgren J (1998) High occupancy vehicle lanes: Not always more effective than general purpose lanes. *Transportation Research Part A: Policy and Practice* 32(2):99–114.

Dunning T (2012) *Natural experiments in the social sciences: a design-based approach* (Cambridge University Press).

Girotra K, Terwiesch C, Ulrich KT (2007) Valuing r&d projects in a portfolio: Evidence from the pharmaceutical industry. *Management Science* 53(9):1452–1466.

Giuliano G, Levine DW, Teal RF (1990) Impact of high occupancy vehicle lanes on carpooling behavior. *Transportation* 17(2):159–177.

Li J, Netessine S (2020) Higher market thickness reduces matching rate in online platforms: Evidence from a quasiexperiment. *Management Science* 66(1):271–289.

Martin PT, Perrin J, Wu P, Lambert R (2004) Evaluation of the effectiveness of high occupancy vehicle lanes, report to Utah Department of Transportation.

Poppe MJ, Hook DJ, Howell KM (1994) Evaluation of high-occupancy-vehicle lanes in phoenix, arizona. *Transportation Research Record* 1446.

Shewmake S (2012) Can carpooling clear the road and clean the air? evidence from the literature on the impact of hov lanes on vmt and air pollution. *Journal of Planning Literature* 27(4):363–374.

Staats BR, Kc DS, Gino F (2018) Maintaining beliefs in the face of negative news: The moderating role of experience. *Management Science* 64(2):804–824.

Vanoutrive T, Van De Vijver E, Van Malderen L, Jourquin B, Thomas I, Verhetsel A, Witlox F (2012) What determines carpooling to workplaces in belgium: location, organisation, or promotion? *Journal of transport geography* 22:77–86.

Vickrey WS (1963) Pricing in urban and suburban transport. *The American Economic Review* 53(2):452–465.

Vickrey WS (1969) Congestion theory and transport investment. *The American Economic Review* 59(2):251–260.

Wellander C, Leotta K (2000) Are high-occupancy vehicle lanes effective? overview of high-occupancy vehicle facilities across north america. *Transportation research record* 1711(1):23–30.

Wiseman Y (2019) High occupancy vehicle lanes are an expected failure. *International Journal of Control and Automation* 12(11):21–32.

Zhang Z, Li B (2017) A quasi-experimental estimate of the impact of p2p transportation platforms on urban consumer patterns. *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 1683–1692.

Appendix A: Regression Table for Time Saving (Section 3.6)

Table 7 Regression estimates to show the positive correlation of the time saving with the carpool variables

	OLS Offers Sent by Drivers	OLS Completed Carpools
log(num_navs)	0.6329***	0.3016***
	(0.067)	(0.066)
log(median_km_suggested_with_HOV)	-2.1363***	0.1448
	(0.816)	(0.797)
log(median_km_suggested_without_HOV)	-0.7726	-1.2884
	(0.818)	(0.799)
avg_time_saving	0.0216**	0.0161*
	(0.009)	(0.009)
MK	-2.5201***	-1.6838***
	(0.234)	(0.229)
NH	-0.8812***	-1.1154***
	(0.188)	(0.184)
Hard	4.6642***	1.9281***
	(0.294)	(0.288)
Soft	3.8606***	1.6748***
	(0.302)	(0.296)
Constant	8.5248***	3.6029***
	(0.567)	(0.554)
Observations	990	990
R^2	0.359	0.125
F Statistic	78.40*** (df = 7;982)	19.98*** (df = 7;982)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix B: Regression Tables for Section 4.3

B.1. Netanya–Herzliya (NH)

Table 8 Regression estimates for NH during morning hours

	OLS Offers Sent by Drivers	OLS Offers Sent by Riders	OLS Completed Carpools
Hard	0.3364***	0.6304***	0.0097***
	(0.068)	(0.090)	(0.028)
Soft	0.4245**	0.6961*	0.2706***
	(0.195)	(0.259)	(0.079)
Control 1	-0.0223	-0.7473***	-0.5965***
	(0.037)	(0.050)	(0.015)
Treatment	-0.1440***	-0.5978***	-0.6291***
	(0.037)	(0.049)	(0.015)
Hard × Control 1	-0.0711	0.4023***	0.2502***
	(0.092)	(0.123)	(0.038)
Soft × Control 1	-0.5324**	-0.0982	-0.1864*
	(0.254)	(0.338)	(0.104)
Hard × Treatment	0.3098***	0.3050**	0.2776**
	(0.091)	(0.121)	(0.037)
Soft × Treatment	0.1458	0.5558*	-0.0815
	(0.239)	(0.317)	(0.097)
Constant	1.3988***	1.3089***	0.6795***
	(0.026)	(0.035)	(0.011)
Observations	4,040	4,040	4,040
R^2	0.041	0.132	0.388
F Statistic	21.78*** (df = 8;4031)	76.73*** (df = 8;4031)	7319.1*** (df = 8;4031)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B.2. Herzliya–Netanya (HN)

Table 9 Regression estimates for HN during evening hours

	OLS Offers Sent by Drivers	OLS Offers Sent by Riders	OLS Completed Carpools
Hard	-0.0176	0.2604	0.1686**
	(0.150)	(0.191)	(0.070)
Soft	-0.2608	0.5203	0.3183*
	(0.363)	(0.462)	(0.169)
Control 1	-0.1844*	-0.0059	-0.1687***
	(0.111)	(0.141)	(0.052)
Treatment	0.3412***	1.1129***	0.0633**
	(0.063)	(0.080)	(0.029)
Hard × Control 1	0.2978	-0.4215	-0.2525**
	(0.240)	(0.305)	(0.112)
Soft × Control 1	-0.0589	-0.3012	-0.0912
	(0.809)	(1.029)	(0.376)
Hard × Treatment	1.2406***	0.3771*	0.1064
	(0.163)	(0.207)	(0.076)
Soft × Treatment	1.1089**	0.0896	0.0035
	(0.395)	(0.503)	(0.184)
Constant	1.0533***	0.3361***	0.2882***
	(0.059)	(0.075)	(0.027)
Observations	2,689	2,689	2,689
R^2	0.162	0.138	0.060
F Statistic	64.81*** (df = 8;2680)	53.43*** (df = 8;2680)	21.48*** (df = 8;2680)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B.3. Mavo Ayalon–Kibbutz Galuyot (MK)

Table 10 Regression estimates for MK during morning hours

	OLS Offers Sent by Drivers	OLS Offers Sent by Riders	OLS Completed Carpools
Hard	0.4766***	0.4566***	0.2424***
	(0.076)	(0.092)	(0.037)
Soft	0.0797	0.4396**	0.1564*
	(0.177)	(0.213)	(0.085)
Control 1	-0.1284***	-0.1396**	-0.2559***
	(0.038)	(0.046)	(0.018)
Treatment	-0.3285***	-0.6470***	-0.3453***
	(0.040)	(0.049)	(0.019)
Hard × Control 1	-0.0691	0.1714	-0.0101
	(0.108)	(0.130)	(0.052)
Soft × Control 1	-0.1370	0.2503	0.1174
	(0.266)	(0.320)	(0.128)
Hard × Treatment	0.8764***	0.0632	-0.0613
	(0.103)	(0.123)	(0.049)
Soft × Treatment	0.3912	0.0566	-0.0598
	(0.243)	(0.292)	(0.117)
Constant	1.6660***	1.6333***	0.6326***
	(0.028)	(0.034)	(0.014)
Observations	5,462	5,462	5,462
R^2	0.081	0.059	0.092
F Statistic	59.91*** (df = 8;5453)	42.73*** (df = 8;5453)	68.75*** (df = 8;5453)

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.