Should I Stay or Should I Go?
Equilibrium Selection in a Transportation Network

Enrica Carbone, Vinayak V. Dixit, and E. Elisabet Rutström

CEAR Working Paper 2020-05
February, 2020

Abstract

When imposing congestion pricing in a transportation network, especially around city centers, there is an expressed concern that commercial activities will have to consider relocating. Such relocations can be both risky and costly. Charges that are aimed at shifting traffic out of downtown areas during times of days when congestion is worst have been implemented in several cities and studies show that drivers often respond very quickly to such price changes, but the effects on commercial activities are less understood. We design an experimental game where merchants predict how drivers will respond before selecting locations. The game is a binary location choice experiment involving introduction of and changes in toll charges around city centers. We model a level of toll charges that implies multiple equilibria and implement two treatments that differ in the history of experiences with toll charges to test its effect on equilibrium selection. We reject the SPNE prediction that merchants make location decisions randomly and commuters follow. Instead, our observations suggest that merchants expect commuters to take out-of-equilibrium actions in order to influence the equilibrium selection. We also find that commuters employ costly signaling actions to make this happen. Finally, our data suggests that history matters somewhat to how players react to a change in the toll charge, imposing friction into the adjustment process, but not affecting the equilibrium selection.

*Corresponding author*. Professor of Economics, Department of Political Science “Jean Monnet”, Università della Campania “Luigi Vanvitelli”, Caserta, Italy. Email: enrica.carbone@unicampania.it

**Professor, School of Civil and Environmental Engineering, University of New South Wales, Australia.**

***Program Director, Center for Economic Analysis of Risk, Georgia State University, Atlanta GA 30309, USA; Guest Professor, Department of Economics, Örebro University, and Affiliated Professor, Department of Economics, Stockholm School of Economics, Sweden; Honorary Professor, Department of Economics, University of Cape Town, South Africa (Rutström). Email: erutstrom@gmail.com.

Acknowledgments: We are grateful to Glenn Harrison, Essam Radwan and Rami Harb for their input and comments at early stages of the research, and to US Federal Highway Administration for funding under Cooperative Agreement DTFH61-09-H-00012.
Declarations

**Funding** provided by the US Federal Highway Administration under Cooperative Agreement DTFH61-09-H-00012.

**Conflicts of interest/Competing interests**: none for either author.

**Availability of data and material**: Data and instructions will be uploaded to journal web site if accepted for publication. Instructions are currently available in online appendix B, available at https://cear.gsu.edu/wp-2020-05-should-i-stay-or-should-i-go-equilibrium-selection-in-a-transportation-network/.

**Code availability**: Codes will be made available on journal web site if accepted for publication.

**Authors’ contributions**: Not applicable

**JEL Classifications**: C72 Noncooperative Games  D9 Micro-Based Behavioral Economics  R41 Transportation: Demand, Supply and Congestion  R48 Government Pricing and Policy
1. Introduction

When imposing congestion pricing in a transportation network, especially around city centers, there is an expressed concern that commercial activities will have to consider relocating. Such relocations can be both risky and costly. In an effort to investigate responses to the introduction of and changes in toll charges around city centers we design a binary location choice experiment involving two types of players: merchants and driving commuters. We model a level of toll charges that implies multiple equilibria and implement two treatments that differ in the history of experiences with toll charges to test its effect on equilibrium selection. It is reasonable to assume that merchants need more time to make investment decisions than commuters need to change travel routes, so we model the game as sequential with merchants moving first, having to anticipate commuter responses. In this game, the Subgame Perfect Nash Equilibrium (SPNE) predicts that the merchants will choose actions randomly, and that commuters will follow the merchants. We investigate the extent to which this prediction is affected by behavioral factors, such as adjustment frictions influenced by history of experiences, and the potential for out-of-equilibrium signaling behavior. Behavioral effects of history have been demonstrated for example in Johnson, Rutström, and George (2006) in a negative externality game and in Cooper and Van Huyck (2016) in a coordination game. Compared to experimental testing of game theoretic models where the payoff consequences of strategy choices are very transparent, often presented as easy to read payoff matrices, this experiment introduced a less transparent but, for the transportation motivation, more realistic information setting. Such lack of transparency generates games where information over time becomes asymmetric since experiences are not shared. Asymmetry in information opens up the possibility of signaling (Cooper, Garvin, and Kagel (1997), Potters, Sefton, and Vesterlund (2007)). The game also has a larger number of players than most theory testing experiments, motivated by increasing realism and external validity.

The motivation for the game comes from concerns within transportation policy debates regarding effects of congestion pricing, particularly the relocation of commercial activities. Businesses often have to plan relocations before they know with any certainty how traffic will change and therefore where their customers will be. This creates the risk that they will make decisions that are ex post suboptimal. In addition, the imposed congestion price levels may not be stationary since determining optimal charges can be difficult and lead to later adjustments by toll authorities. Thus, when authorities are planning pricing levels they have to anticipate how drivers will respond, not only to the initial price levels, but also to subsequent price adjustments. If the initial price level is set too high, and target traffic flows are not achieved, subsequent price changes may not result in the same final outcome as if the initial price level was set accurately. In this paper we investigate equilibrium selection as a function of prior experiences with different price levels, thus modeling the adjustment process after initial toll charges or charge corrections are announced.

Charges that are aimed at shifting traffic out of downtown areas during times of days when congestion is worst have been implemented in Singapore in 1975, in London in 2003, and in Stockholm in 2006. In Stockholm at the introduction the charges were set at a level intended to reduce traffic by
10-15% but immediately lead to a 22% reduction that has been sustained in the long run (Eliasson (2014), Eliasson et al. (2009)). A temporary removal of the charge system after 6 months quickly returned traffic to close to previous levels. Both average travel times and the dispersion of travel times were reduced by 1/3 to 1/2. This demonstrates that congestion charges can be effective ways of reducing congestion in downtown areas. Field experiments confirm these behavioral effects but also make it clear that drivers have many other considerations than congestion charges that affect how they respond. Ben-Elia and Ettema (2011a,b) gave Dutch commuters rewards for reducing their use of the Zoetermeer-The Hague corridor during peak hours and report significant changes in behavior. However, Nielsen (2004) and Nielsen and Sørensen (2008), used time varying charges across zones in Copenhagen and conclude that there is a great deal of heterogeneity in what motivates each trip and each participant.

There have been a number of lab experiments looking at route choice equilibria and adjustment paths after introducing congestion pricing. Using a lab setup with driving simulators Dixit et al. (2015) and Tsang (2015) show that both student participants and field participants recruited from a commuting population react to changes in risk as well as changes in charges under conditions of both risk and uncertainty. Apart from these individual choice experiments there are also some interactive lab experiments on route choice. Selten et al. (2007) conduct a repeated route choice experiments with groups of 18 where congestion is endogenously determined. The game has multiple pure strategy equilibria and thus involve coordination across the drivers. All equilibria imply the same distribution of the traffic volume and the same symmetric payoffs. They find a great deal of heterogeneity in responses with two dominant modes: a direct response mode where route switches occur immediately following an experience of congestion, and a contrary response mode where a route switch does not occur following an experience with congestion, consistent with the respondent instead expecting others to switch so that congestion will ease. Chmura and Pitz (2007) conducted a repeated route choice game with groups of 6 and similarly found great variation in behavior. In their coordination game the payoffs are discrete but endogenous. Those who chose the relatively less crowded option got a payoff of 1, and those who chose the relatively more crowded option got nothing. They also did a variation with very large groups (18 through 90) and payoffs that vary with congestion as well as with the route choice. Anderson, Holt and Reiley (2008) report on an experiment with both exogenous and endogenous congestion pricing. None of these experiments on congestion pricing investigate the effects on commercial activities or the effects on interactions between different types of players.

Based on the data from our experiment, we reject the SPNE prediction that merchants make location decisions randomly and commuters follow. Instead, our observations suggest that merchants expect commuters to take out-of-equilibrium actions in order to influence the equilibrium selection. We also find observations of commuters employing costly signaling to make this happen. Finally, our data suggests that history matters somewhat to how players react to a change in the toll charge, imposing friction into the adjustment process, but not affecting the equilibrium selection.
The next section will describe our experimental game and the predictions we make assuming payoff maximizing behavior. Section 3 discusses our findings, and section 4 concludes.

2. The experimental game

2.1 Design

The experiment consists of a repeated, sequential network game with merchants moving first, followed by commuters. It was carried out using z-Tree. The network is shown in Figure 1. There are two merchants who independently and simultaneously choose between a downtown and a perimeter location in the network. It is possible for the downtown location to accommodate both merchants, but if they choose the perimeter they cannot be in the same perimeter location. Since there are two perimeter locations they will be randomly assigned to one of them, conditional on choosing the perimeter. There are either 6 or 8 commuters, the numbers vary across sessions. Half of the commuters start the game from a north network location (suburb), with the goal of commuting to the south to work in the morning and then commute back north to home in the afternoon. The other half of the commuters start from a south location with the reverse commuting directions. The downtown route is two-way so if both north and south commuters take that route they all contribute to the congestion. The perimeter route is one-way, running clockwise, so congestion is only affected by the commuters that originate in the same location. The experiment is conducted under three conditions, varying the cost of passing through downtown for commuters. The charges are $0, $3, and $4, respectively. There are two treatment conditions: treatment 1 consists of commuters first participating in ten rounds with a $0 charge, followed by another ten rounds with a $3 charge. Treatment 2 consists of commuters first participating in ten rounds with a $4 charge, followed by another ten rounds with a $3 charge. The first ten rounds generate a different experience in the two treatments that is hypothesized to influence behavior in the $3 charge condition. These treatments model situations where toll authorities infer that the initial charges are suboptimal, too low in treatment 1 and too high in treatment 2, and decide to adjust them.

Merchants make profits by selling to commuters who pass them by during the afternoon commute. In the sessions with 8 commuters a merchant makes a 50 cent profit for each commuter that shops from him. In the sessions with 6 commuters a merchant makes a 75 cent profit per shopper. The higher per unit sale revenue was designed to compensate for the smaller number of commuters to generate the same equilibrium predictions. If a merchant is located on the southbound perimeter it is the south commuters doing the shopping if they take the perimeter in a southward direction in the afternoon. If the merchant is located on the northbound perimeter his shoppers are the north commuters. If the merchant is located in the downtown both north and south commuters can shop from him. However, if

1 Fischbacher (2007).
2 The reason for having two group sizes was purely logistical. We recruited for the larger size but were able to still run the session if fewer participants showed up. We do not find a significant difference in behavior across group sizes and therefore pool them in the analysis reported here.
both merchants are in the downtown they will share the commuters equally. Shoppers cannot choose which merchant they shop from if both are in the downtown and all commuters must shop during the afternoon commute. The maximum profit for a merchant on the perimeter is $2 and $2.25 in the 8 and 6 commuter sessions, respectively. In the downtown the maximum profit is $4 and $4.50, respectively, in the case where the other merchant chose the perimeter but all commuters go through downtown.

Commuters receive a $3 endowment in each round, referred to as a wage. When they shop they get additional value. They may shop from one of the merchants, earning them another $4, but if they take a route where there is no merchant, their shopping value is only $2 on the perimeter or $3 in the downtown. In the instructions this is explained as the human merchants selling superior goods compared to default simulated merchants who sell inferior goods. Commuters incur a travel cost both in the morning and in the evening. For each second the commute takes they are charged 1 cent. Table 1 shows how travel times are affected by the commuter’s route choice conditional of what other drivers are doing. These travel times were generated in advance using the Vissim traffic simulator in order to create conditions that are consistent with actually occurring traffic. Past experiments on route choice, departure time choice, or mode choice, have used travel times that were induced as a simple linear function of the number of participants making each choice. By using a simulation to generate such travel times we added a stochastic element, resulting in a non-linear relation between traffic volume and travel times. Participants were shown a table of the non-linear travel times that would result from various levels of congestion. In addition, simulating travel times did not result in the same travel times on both sides of the perimeter route, for any given level of congestion, which is why the travel cost is listed separately for north- and southbound traffic. It is clear from Table 1 that taking the perimeter route results in longer travel times than taking the downtown route. The difference in travel time between the two routes, conditional on the choices of the other commuters, is shown in the last two rows of the table. The difference in travel time on each route due to congestion generated by the other

---

3 In order to generate salient congestion effects we modeled a number of simulated vehicles that copy the route choice of each commuter. The number of simulated plus human operated vehicles is the same for both group sizes. This implies that the travel times for any route choice distribution are the same.


5 The stochastic nature of travel times is generated by each vehicle in the simulation departing at a random time and having a random travel time (within specified bounds). Participants were told that the simulation software used to generate the travel times “is the same that many traffic engineers use when they are planning transportation routes”. They were also shown one simulation as an example. In this example 75% of the north commuters and 25% of the south commuters go through the downtown. In order to create congestion in the simulation it was necessary for each participant’s choice to affect more than one vehicle. We thus simulated additional vehicles that simply followed the same route as the vehicle that the participant controlled. Thus, the effect of one driver deviating from the choices of others had a stronger effect on travel times than it would have if no other vehicles followed the choice of that driver. In the sessions with 8 commuters there were 5 simulated vehicles that followed the participant’s route choice, and in the sessions with 6 commuters there were 7 simulated vehicles that followed the participant’s route choice. In either case there were a total of 48 vehicles so that the possible congestion is the same across all sessions. Notice that the subject only affects the route choice of the simulated vehicles that follow his vehicle, not its speed or departure time. Each of these vehicles had its own actualization of the random speed and departure time. Travel times were not stochastic in real time since the traffic scenarios were simulated in advance of the experimental sessions.
commuters is shown in the last column of the table. These columns showing differences were not shown to participants.

Finally, if commuters go through downtown they have to pay the charge, with the amount depending on what condition they are in. The commuter earnings can therefore be specified as:

$$\pi_{c,j} = w + s_{i,j} - c_{t,j} - \tau_{R,j}^{AM} - \tau_{R,j}^{PM}$$

where $w$ is the wage of $3, $s_i$ is the shopping value conditional on $i = \{\text{inferior perimeter, inferior downtown, superior}\}$, $c_t$ is the charge conditional on treatment $t = \{\$0, \$3, \$4\}$, and $\tau_{p}^{AM}$ and $\tau_{p}^{PM}$ are the travel time costs in the morning and the afternoon, depending on route $R = \{\text{northbound perimeter, southbound perimeter, downtown}\}$ and how many other commuters are on the same route at that time, with $j$ indexing each drive event.  

2.2 Predictions

We make predictions for the commuter subgame first, separately for each level of charges, for entering the downtown. First we notice that the predictions for the morning commute to work are easy to make. If the charge to enter the downtown is $0$, then the choice is simply to take the route with the shortest travel time, which is always the downtown. If the charge is $3$ or $4$ it is the perimeter since the charge exceeds the additional travel time cost on the perimeter. Thus we focus here on the predictions for the afternoon commutes when shopping occurs.

In the afternoon, the predictions for commuters depend on the relative earnings of the two routes. The condition for choosing the perimeter is that, for a drive $j$, the net earnings on the perimeter, subscript $p$, is greater than the net earnings in downtown, subscript $dt$:

$$\pi_{p,j} > \pi_{dt,j}$$

Using the earnings equation (1) we can write (2) as

$$s_{p,j} - \tau_{p,j} > s_{dt,j} - c_{dt,j} - \tau_{dt,j}$$

Rearranging the terms we get

$$s_{dt,j} - s_{p,j} - (\tau_{dt,j} - \tau_{p,j}) < c_{dt,j}$$

---

6 Instructions given to participants are reproduced in online appendix B which can be found at https://cear.gsu.edu/wp-2020-05-should-i-stay-or-should-i-go-equilibrium-selection-in-a-transportation-network/.

7 The implied payoffs for north- or southbound travel in the mornings is shown in Table A1 and A2 in Appendix A, available at https://cear.gsu.edu/wp-2020-05-should-i-stay-or-should-i-go-equilibrium-selection-in-a-transportation-network/.
The second term of the LHS is always negative; commuters save in travel time cost by going through
downtown. The first term is positive whenever merchants are in downtown generating superior
shopping value there, and negative whenever merchants are not in downtown so that the shopping
value there is inferior. When the shopping value in downtown is superior the LHS is greater than when
the shopping value in downtown is inferior, thus a higher cordon charge is required in order for
commuters to select the perimeter route. Thus, when the cordon charge is high enough, as in our $4
case, the commuters have a dominant strategy to choose the perimeter route, i.e. they will choose the
perimeter even when the merchants are in downtown. Similarly, when the cordon charge is low
enough, as in our $0 case, the commuters have a dominant strategy to choose the downtown route, i.e.
they will choose the downtown even when the merchants are on the perimeter. Because the predictions
in the $0 and $4 cases are so different they generate very different histories for commuters before they
start the $3 case.

The predictions for merchants are easy for the cases with the very high and very low cordon
charges, since the dominant strategies of the commuters imply that merchants will locate on the
dominant route. When the cordon charge is intermediate, as in the $3, we will show that there are
multiple equilibria. In this case, we hypothesize that the equilibrium selection will depend on prior
experiences that come from participating in a dominant strategy game first. We now turn to the
predictions for the $3 case, which has multiple equilibria.

Table 2 shows the payoffs to north commuters when the charge for entering the downtown is $3.8
In this condition commuters do not have dominant strategies, but their optimal choices depend on what
the merchants do. Let us start by looking at the payoffs in the top part of the table, where all south
commuters are assumed to go through downtown, as shown in Column 3. As long as there is no
merchant on the northbound perimeter (columns 4 and 5), the typical north commuter prefers the
downtown route, even if all other north commuters do the same.9 Thus, even when all commuters, both
south and north, go through downtown, it is the best north route choice, as long as there is no merchant
on the northbound perimeter making that route more attractive.

Comparing the numbers in columns 4 and 5 to those in column 6, which has a merchant on the
northbound perimeter, we see a higher shopping value on the perimeter in the latter case. This changes
the optimal choice for the north commuter such that the perimeter is a dominant strategy in the

---

8 The pattern of payoffs for south commuters is the same, and thus leads to the same predicted behavior. The payoff table for south commuters can be found in online Appendix A1 at https://cear.gsu.edu/wp-2020-05-should-i-stay-or-should-i-go-equilibrium-selection-in-a-transportation-network/.

9 As the number of commuters through downtown decreases, the difference in payoffs between the downtown and the perimeter option gets larger, strengthening the incentives to take downtown. We can see this travel time cost reduction by comparing the last eight rows, where no south commuters are in downtown (Column 3), to the top eight rows where they are all there. Without any south commuters in downtown the incentives to go through downtown strengthens further due to reductions in travel time costs. The largest incentive to go through downtown is found for row pair 5 (0 other north commuters in downtown and 0 south commuters in downtown). The difference in payoffs between downtown and the perimeter then is $1.07. The smallest incentive is found for row pair 4 (3 other north commuters in downtown and 4 south commuters in downtown). The difference is then $0.47.
subgame between commuters. The strength of this preference weakens with the number of both northbound and southbound commuters on the perimeter due to additional congestion. Comparing column 7 with both merchants on the perimeter to column 6 we see a $1 drop in shopping value in downtown, reflecting the availability of inferior goods only. This further strengthens the preference for the perimeter and the perimeter choice is still the dominant strategy in the subgame. The strength of this preference weakens with the number of both northbound commuters on the perimeter due to additional congestion, but not so much that the route is not the preferred one. Recall that southbound commuters are on the other side of the perimeter and do not affect congestion on the northbound side.

We conclude that as long as there is a merchant on the side of the perimeter that the commuter would drive on, the commuter is better off on the perimeter than in downtown. Otherwise, the commuter is better off in downtown.

Thus, in the $3 case the optimal choice for the commuters depends on what the merchants do. Table 3 shows the payoff matrix to the merchants corresponding to the $3 case. If both merchants are in downtown, both northbound and southbound commuters will go through downtown and both businesses will sell 4 units. If both merchants are on the perimeter, both types of commuters will take the perimeter route, and both businesses will sell 4 units. When one merchant is on the northbound perimeter and the other in downtown, the north commuters will take the perimeter and the south commuters will go through downtown, and both businesses will sell 4 units. Finally, if one merchant is on the southbound perimeter and the other in downtown, the south commuters will take the perimeter and the north will go through downtown, and both businesses will sell 4 units. Thus, the merchants are completely indifferent between the location choices, since any choice they make will generate a subgame with dominant strategies for all commuters. Table 4 then shows the payoffs to the commuters for the four different pure strategy equilibria of the game. This table shows that commuters have a preference for the perimeter equilibrium, which is also more efficient than the others.

Thus we do not have a unique prediction for this game. We are interested in investigating equilibrium selection, particularly the role that history may have in the selection. One may think of several factors that motivate equilibrium selection in a setting such as this. In the SPNE merchants would choose location randomly, and commuters would simply follow that choice. Thus, we would expect to see each of the four possible outcomes associated with the equilibria (all in downtown, all on the perimeter, south commuters in downtown with north commuters on the perimeter, and north commuters in downtown with south commuters on the perimeter) played ¼ of the time. However, the experimental literature on equilibrium selection indicates behavioral and cognitive factors that can influence selection. For example, the merchants may exhibit social preferences that affect their strategy choices, or commuters may choose not to play their subgame dominant strategies in attempts to force merchants to change to a preferred equilibrium. History, in terms of payoffs experienced during the early 10 periods, may influence play if commuters are primarily adaptive with little sophisticated reasoning. We expect that the downtown dominant strategy during the early 10 periods of treatment 1 would provide a behavioral pull on the downtown equilibrium in the late 10 periods, and
similarly that the perimeter dominant strategy during the early 10 periods of treatment 2 would provide a behavioral pull on the perimeter equilibrium in the late 10 periods. Jiao (2016) show that experiences of gains from certain actions can induce more optimism regarding the success of such actions in the future.

2.3 Experimental procedures

The experiments were conducted in February and March 2013 in the ExCen lab at Georgia State University. There are 42 networks, half of them with 6 commuters and the other half with 8 commuters, for a total of 294 participants. Half the networks were conducted as treatment 1, starting with 10 periods of $0 charge for entering downtown followed by 10 periods of $3 charge. The other half of the networks were conducted as treatment 2, starting with 10 periods of $4 charge followed by 10 periods of $3 charge. The group sizes are close to equally distributed across the two charge treatments.10

3. Results

3.1 Results from morning drives without shopping

While the afternoon drives are of most interest, we will briefly discuss the choices observed during the mornings here. For the morning drives we find strong support for the dominant strategy equilibria in all cases. Only the $3 case with a history of $0 has a unique deviation in period 12 where we observe a discrete drop in the propensity to choose the predicted perimeter route and consequently higher proportion of commuters in downtown.

Figure 2 shows the proportion of commuters who took the perimeter route in the mornings, pooled across all sessions within each treatment, by period. The only parameters that influence morning commute choices are travel times and toll charges, since there is no shopping value. Figures 2a and 2c show treatment 1, where the first 10 periods have a $0 charge and the prediction is for all to take the downtown route. Figure 2a shows that there are no sessions in which all commuters take the perimeter route in any period, and Figure 2c shows that the proportion of commuters on the perimeter route is small and decreasing across periods. The downtown route attracts 74% of the commuters in period 1 and 89% on average across all periods. We conclude that the observations on commuters in the $0 periods support the equilibrium prediction. Figures 2b and 2d show treatment 2, where the first 10 periods have a $4 charge and where the perimeter is the predicted route. While initially very few sessions have all commuters on the perimeter, as shown in Figure 2b, the proportion of commuters shown in Figure 2d starts as high as 75% in period 1, and increases steadily. Again we find support for the dominant strategy equilibrium.

---

10 There are 11 sessions in treatment 1 with 6 commuters and 10 with 8 commuters. There are 10 sessions in treatment 2 with 6 commuters and 11 with 8 commuters. No significant differences due to group size are found.
The last 10 periods in all Figures 2a-d have a $3 charge and the perimeter is the predicted route for the morning commutes. In Figure 2c we see an immediate attraction to the perimeter in period 11 with 90% of the commuters choosing that route, despite just having experienced the downtown equilibrium. However, this weakens temporarily in period 12 and then reemerges sequentially over periods 13 and 14 so it appears that the commuters are somewhat uncertain about the optimality of choosing the perimeter. The period 12 drop in perimeter choice is a phenomenon that is consistent across 17 of the 21 sessions in treatment 1, so this is not just one or two sessions, it is a common pattern. This pattern is unique to this treatment, but appears both in the morning and the afternoon drives. In the $3 case with the $4 history (the last 10 periods of treatment 2) the prediction is, again, for all commuters to choose the perimeter route. In Figure 2d we see almost no interest in the downtown route even in the beginning so in this treatment drivers are more certain of the route optimality, having experienced that equilibrium during the first 10 periods.

We conclude that morning commuters, who are not motivated by shopping values, behave in predicted ways based on the toll charges and travel costs that they face. The $3 case with the $4 history has the highest proportion of commuters taking the predicted route (averaged over periods), which in that case is the perimeter. In treatment 1 the toll charge changes the optimal choice, and commuters choose the perimeter a bit less often on average.11 Thus, there also seems to be an influence from prior experiences.

3.2 Results from afternoon drives with shopping

Our main interest is in the afternoon drives where the commuters are shopping on the way home. In the afternoon payoffs depend not only on travel times and downtown toll charges, but also on shopping values that depend on the location of merchants. Figure 3 shows the proportion of sessions with all commuters on each route in the afternoon and the proportion of commuters on each route in the afternoon, by period, for treatment 1. Figure 3a shows the proportion of sessions with all commuters in downtown, and Figure 3c shows the proportion of commuters in downtown. Similarly, Figure 3b shows the proportion of sessions with all commuters on the perimeter, and Figure 3d shows the proportion of commuters on the perimeter. Obviously, Figure 3d is simply the mirror image of Figure 3c. Figure 4 shows the same thing for treatment 2.

During the first 10 periods, with charges of $0 and $4, the patterns are very similar to those in the morning, supporting the dominant strategy equilibria. In the $0 case (Figure 3c) the maximum proportion of commuters in downtown is found in period 6 and is 99%. In period 1 the proportion is already 68% and there is not a single period and session in which all commuters go through the equilibrium during the first 10 periods.

11 More detailed discussions of results can be found in online Appendix A, which can be found at https://cear.gsu.edu/wp-2020-05-should-i-stay-or-should-i-go-equilibrium-selection-in-a-transportation-network/.
perimeter (Figure 3b). In the $4 case (Figure 4d) the maximum proportion of commuters on the perimeter is found in period 10, and it is an astounding 100%. Every single commuter takes the perimeter route. Again, there is not a single period in which all commuters go through downtown (Figure 4a).

3.2.1 Results for the multiple equilibria case

Having verified that behavior is close to prediction in the conditions with dominant strategies, we now turn to the last 10 periods of the afternoon drives for both treatments, where we have multiple SPNE. The predicted commuter route choices now depend on where the merchants locate, and the merchants themselves are indifferent, as long as they expect commuters to follow them. The SPNE predicts that merchants should choose location randomly, since the best response for commuters is to follow. Eyeballing Figures 5c, 5d, 6c and 6d this is clearly not the case: the proportions of merchant location choices are far from 50/50. On average across periods 11-20 the proportion of merchants in downtown is 22% in treatment 1 and 8% in treatment 2. Clearly the merchants are not choosing randomly, but rather favoring the perimeter equilibrium. Since their own payoffs are completely independent of which equilibrium they are in, something else must be motivating this choice.

A hint at the motivation for selecting the perimeter is found in treatment 1 where we see that there is a sharp drop in the merchant selection of downtown in Period 11 (Figures 5a and c, and Figures 3a and c). Thus immediately after learning about the imposition of the toll charge, merchants appear to expect that commuters favor a shift to the perimeter. The fact that merchants are affected by this expectation reflect either some fairness preference or a strategic recognition that commuters may not follow them to downtown. Prasnikar and Roth (1992) discuss the role of such considerations in Ultimatum and Best Shot Public Goods games. They conclude that first movers seem to recognize the strategic possibility of second movers acting in ways not predicted by SPNE, and this anticipation makes them adapt their strategies so as to avoid losing earnings in the out-of-equilibrium consequences. Prasnikar and Roth (1992) and Potters, Sefton and Vesterlund (2007) find evidence in favor of self-interested strategizing rather than fairness are able to reject fairness motivated play by first movers, in favor of such strategic adaptation. Cooper and Kagel (2008) investigate a signaling game and find that a fair proportion of subjects are sophisticated enough to anticipate responders’ behavior after a change in payoff structures. These previous results plus the difficulty merchants face if calculating payoffs to commuters leads us to put very little probability on this explanation of merchant behavior. Next we instead look at the possibility that merchants react strategically to the possibility that commuters will not follow them to downtown.

After the drastic drop in selection of downtown in period 11 merchants return somewhat to the Downtown in period 12-14, but this trend is ultimately abandoned in period 15 and beyond (Figure 5c). If merchants are correct in their expectations of how commuters may not follow them to downtown, we
should be able to see this during those periods. In fact, Figures 3c and 3d show exactly that. While there is an increase in the commuter propensity to go to downtown in period 12, this is very temporary and commuters return to the perimeter quicker than do merchants. During periods 11-20 there are 132 instances (9%) in which a commuter takes the perimeter route even though no merchant is located there. The average earnings across those instances is -$0.58, thus a direct loss from such actions. To judge the extent to which these instances simply reflect the kind of errors and trembles we often see among experimental subjects, we compare this propensity to that of commuters taking the Downtown route even when there is no merchant in downtown. Taking the downtown route without a merchant being there must be considered an error since the loss in shopping value plus the toll charge would result in significantly lower earnings than in the perimeter equilibrium. During the same periods there are only 26 instances of such play (1.8% of observed choices). While the difference between these proportions is not strongly significant, it does suggest that there may be a willingness to send costly signals about the desirability of the perimeter. The average earnings of commuters who are neither signaling nor making errors is $1.08 per period. The total cost of a signal is therefore on average $1.66, the foregone earnings of following the merchant to downtown plus the additional travel time cost of taking the longer perimeter route. The gain to commuters in the perimeter equilibrium compared to the downtown is $1.22 so the signaling cost can be recovered within two periods of perimeter play. Brandts and Holt (1003) report on costly signaling in asymmetric information games. While in a strict sense we do not have asymmetric information in this game, since all players are equally, but not fully, informed about all payoff variables, we do have an experiential asymmetric information condition. All payoff feedback is strictly private so commuters will know more about their payoff consequences of route choice equilibria then merchants. Costly signaling is also observed in voluntary contribution games as a way for one designated player to lead the game into a more efficient outcome (Güth, Levati, Sutter, and van der Heijden (2007), Potters, Sefton and Vesterlund (2007)).

What are the payoff consequences to the merchants who locate in the downtown when commuters do not follow? There are no periods in which a merchant locates in downtown and no commuters are following, so merchants always make some sales and earnings are always positive. The average earnings on the perimeter for merchants is $2, while it is $1.50 in downtown. Thus, the incentive for these merchants to react to the commuter signals is to try to regain the lost 50 cents.

Since payoffs are not fully transparent, but are learnt privately over time, the expectation of commuters choosing the perimeter route in period 11 of treatment 1, immediately after the imposition of the $3 charge, is likely based on other considerations. One such possibility would be merchants having a model of commuters that assumes a low sophistication in reasoning or a low attention level. For example, commuters may be making their decisions only on the toll charge, disregarding other payoff variables. If so, the merchant would expect commuters to take the downtown route only in the

12 The p-value in a one-sided Fishers exact test is 0.083.
$0 case, and to take the perimeter route when the toll charges are $3 or $4. This is exactly the pattern we see in our data, and play in the early periods are particularly suggestive of this.

Since, by design, payoffs are not transparent in this design, it is possible that history plays an important role in behavior and that play over time is influenced by actual payoff experiences. All players received complete feedback about their own total payoffs and the breakdown of the payoffs into its components after each period. Over time players can therefore learn which equilibria are the most favorable to them. Table 4 shows the afternoon payoffs to north and south commuters based on the assumption that merchants perfectly anticipates their choices. This deformation of the game to a game between commuters implies a unique Nash Equilibrium on the perimeter. For periods 11-20, when the toll charge is $3, actual payoff experiences by commuters would strengthen the attraction to the perimeter, if initial selection is based simply on toll charges. Thus, looking only within the $3 condition it would be difficult to detect history effects. However, the reactions to the change in toll charges in period 11 would be affected by their history during the first 10 periods. Our treatments were designed with detecting such effects in mind.

The history variable of interest to the commuters in treatment 1 is the profitability of the downtown route, and in treatment 2 it is the profitability of the perimeter. These different histories could influence route choice when the toll charge changes to $3. Consistent with Jiao (2016) who found that positive past experiences can make agents overly optimistic about the continued success of past actions after a regime shift, we see some evidence of this. During periods 11-15 the propensity of commuters to choose downtown in treatment 1 (16%) is significantly higher than in treatment 2 (5%), see Figures 3c and 4c. We also see a significantly higher propensity for merchants to choose downtown in treatment 1 (22%) than in treatment 2 (8%), during the same periods, see Figures 5c and 6c. During these periods we also see a significantly higher propensity for commuters to signal the perimeter in treatment 1 (9%) than in treatment 2 (4%).13 Due to the greater propensity to signal and the friction on the adjustment path that is due to history, efficiency in the $3 condition is lower in treatment 1 than in treatment 2.

We conclude that while initial play may be influenced by low sophistication reasoning, subsequent play seems influenced by payoff experiences. While commuters engage in some costly signaling, it does not take much to influence the merchants, who, themselves, are indifferent between the equilibria.

4. Summary and Conclusions

We design and implement an experiment with a finitely repeated sequential game between merchants and commuters to investigate responses to changes in toll charges. If toll charges are effective at moving traffic out of congested city centers then merchants who remain would lose demand. It is reasonable to assume that merchants need to more time to make investment decisions than commuters need to change travel routes, so we model the game as sequential with merchants moving first. Compared to experimental testing of game theoretic models where the payoff

13 All significance tests are Fisher’s exact test with p < .001.
consequences of strategy choices are very transparent, often presented as easy to read payoff matrices, this experiment introduced a less transparent but more realistic information setting. In this setting all players are given common information about components of payoffs that stay constant throughout the game, such as shopping values and toll charges. Travel time costs, however, are endogenous and vary across routes. Since we use a stochastic simulation model to generate travel times, these are not linear functions of congestion, but all participants are given common information about these travel times in the form of a handout table. It is clearly more difficult for participants to form payoff expectations than in experiments with simple payoff matrices. There are more than two commuters so coordinated actions within the commuter group during learning periods is difficult and out-of-equilibrium actions are expected.

We implement two treatments in the experiment to test if the history of play affects equilibrium selection. The equilibrium selection game is played out during the last 10 periods in both of the treatments. The initial 10 periods generate the different histories based on dominant strategies. The equilibrium selection game has multiple SPNE with the merchant being completely indifferent between them since commuters would always take the route that merchants locate on.

We reject strict SPNE play which predicts that merchants choose locations randomly and commuters follow. Instead, our observations suggest that merchants expect commuters to take out-of-equilibrium actions in order to influence the equilibrium selection. We also find observations of commuters taking such costly signaling actions to make this happen. Finally, our data suggests that history matters somewhat to how players react to a change in the toll charge, imposing friction into the adjustment process, but not affecting the equilibrium selection.

What are the implications for traffic planning from these findings? We find that the $3 toll charge is more successful at directing traffic and commercial activities to the perimeter from downtown than what is predicted by the SPNE. Thus, when we introduce a positive toll charge when there has been none in the past its success is partly explained by the willingness of commuters to disregard merchant locations and the ability of merchants to anticipate this. If the toll charge is set too high in historic periods, as in the $4 condition, adjusting it down does not generate a large adjustment cost, and commuters and merchants simply remain on the perimeter. These findings support the observations of quick adjustments in previous route choice experiments in the lab, as well as the field experiments and trials conducted in Stockholm and elsewhere. Here we also see that merchants anticipate commuter reactions to the change in the toll charge, so that coordination on the more efficient equilibrium happens quickly.

References


Cooper, David J. and John Van Huyck. 2016. “Coordination and Transfer”, Unpublished Manuscript, Department of Economics, Florida State University, August 30.


Figure 1: The Network

![Network Diagram]

Table 1: Travel Time Costs:

<table>
<thead>
<tr>
<th></th>
<th>All other drivers take downtown</th>
<th>All other drivers take perimeter</th>
<th>Difference due to congestion on the route</th>
</tr>
</thead>
<tbody>
<tr>
<td>Southbound downtown</td>
<td>$1.15</td>
<td>$0.95</td>
<td>$0.20</td>
</tr>
<tr>
<td>Northbound downtown</td>
<td>$1.25</td>
<td>$1.00</td>
<td>$0.25</td>
</tr>
<tr>
<td>Southbound perimeter</td>
<td>$2.35</td>
<td>$2.50</td>
<td>-$0.15</td>
</tr>
<tr>
<td>Northbound perimeter</td>
<td>$2.66</td>
<td>$3.03</td>
<td>-$0.37</td>
</tr>
<tr>
<td>Southbound difference</td>
<td>$1.20</td>
<td>$1.65</td>
<td></td>
</tr>
<tr>
<td>Northbound difference</td>
<td>$1.41</td>
<td>$2.03</td>
<td></td>
</tr>
</tbody>
</table>
Table 2: Typical North Commuter Payoffs with $3 Charge

<table>
<thead>
<tr>
<th>Route choice</th>
<th>Column 1</th>
<th>Column 2</th>
<th>Column 3</th>
<th>Column 4</th>
<th>Column 5</th>
<th>Column 6</th>
<th>Column 7</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number other northbound in downtown</td>
<td>Number southbound in downtown</td>
<td>Both business owners in downtown</td>
<td>One business owner in downtown and the other on southbound (east) perimeter</td>
<td>One business owner in downtown and the other on northbound (west) perimeter</td>
<td>One business owner on southbound (east) perimeter and one on northbound (west) perimeter</td>
<td></td>
</tr>
<tr>
<td>Downtown</td>
<td>0</td>
<td>4</td>
<td>3</td>
<td>3</td>
<td>3</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>Perimeter</td>
<td>0</td>
<td>4</td>
<td>2.17</td>
<td>2.17</td>
<td>4.17</td>
<td>4.17</td>
<td></td>
</tr>
<tr>
<td>Downtown</td>
<td>1</td>
<td>4</td>
<td>2.92</td>
<td>2.92</td>
<td>2.92</td>
<td>1.92</td>
<td></td>
</tr>
<tr>
<td>Perimeter</td>
<td>1</td>
<td>4</td>
<td>2.2</td>
<td>2.2</td>
<td>4.2</td>
<td>4.2</td>
<td></td>
</tr>
<tr>
<td>Downtown</td>
<td>2</td>
<td>4</td>
<td>2.89</td>
<td>2.89</td>
<td>2.89</td>
<td>1.89</td>
<td></td>
</tr>
<tr>
<td>Perimeter</td>
<td>2</td>
<td>4</td>
<td>2.3</td>
<td>2.3</td>
<td>4.3</td>
<td>4.3</td>
<td></td>
</tr>
<tr>
<td>Downtown</td>
<td>3</td>
<td>4</td>
<td>2.81</td>
<td>2.81</td>
<td>2.81</td>
<td>1.81</td>
<td></td>
</tr>
<tr>
<td>Perimeter</td>
<td>3</td>
<td>4</td>
<td>2.34</td>
<td>2.34</td>
<td>4.34</td>
<td>4.34</td>
<td></td>
</tr>
<tr>
<td>Downtown</td>
<td>0</td>
<td>0</td>
<td>3.04</td>
<td>3.04</td>
<td>3.04</td>
<td>2.04</td>
<td></td>
</tr>
<tr>
<td>Perimeter</td>
<td>0</td>
<td>0</td>
<td>1.97</td>
<td>1.97</td>
<td>3.97</td>
<td>3.97</td>
<td></td>
</tr>
<tr>
<td>Downtown</td>
<td>1</td>
<td>0</td>
<td>2.96</td>
<td>2.96</td>
<td>2.96</td>
<td>1.96</td>
<td></td>
</tr>
<tr>
<td>Perimeter</td>
<td>1</td>
<td>0</td>
<td>2.06</td>
<td>2.06</td>
<td>4.06</td>
<td>4.06</td>
<td></td>
</tr>
<tr>
<td>Downtown</td>
<td>2</td>
<td>0</td>
<td>2.87</td>
<td>2.87</td>
<td>2.87</td>
<td>1.87</td>
<td></td>
</tr>
<tr>
<td>Perimeter</td>
<td>2</td>
<td>0</td>
<td>2.15</td>
<td>2.15</td>
<td>4.15</td>
<td>4.15</td>
<td></td>
</tr>
<tr>
<td>Downtown</td>
<td>3</td>
<td>0</td>
<td>2.75</td>
<td>2.75</td>
<td>2.75</td>
<td>1.75</td>
<td></td>
</tr>
<tr>
<td>Perimeter</td>
<td>3</td>
<td>0</td>
<td>2.26</td>
<td>2.26</td>
<td>4.26</td>
<td>4.26</td>
<td></td>
</tr>
</tbody>
</table>
Table 3: Payoff Matrix for the Merchants with $3 Charge

<table>
<thead>
<tr>
<th></th>
<th>B2 in Downtown</th>
<th>B2 in Perimeter</th>
</tr>
</thead>
<tbody>
<tr>
<td>B1 in Downtown</td>
<td>$2.00 / $2.00</td>
<td>$2.00 / $2.00</td>
</tr>
<tr>
<td>B1 in Perimeter</td>
<td>$2.00 / $2.00</td>
<td>$2.00 / $2.00</td>
</tr>
</tbody>
</table>

Table 4: Commuter Afternoon Payoffs with $3 Charge

<table>
<thead>
<tr>
<th>South / North Commuters</th>
<th>Downtown</th>
<th>North Perimeter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Downtown</td>
<td>$2.85 / $2.75</td>
<td>$2.93 / $4.21</td>
</tr>
<tr>
<td>South Perimeter</td>
<td>$4.49 / $2.81</td>
<td>$4.50 / $3.97</td>
</tr>
</tbody>
</table>
Figure 2: Commuters' Perimeter Choice in the Morning by Period

Figure 2a: Proportion of Sessions With All Commuters in Perimeter in Treatment 1

Figure 2b: Proportion of Sessions With All Commuters in Perimeter in Treatment 2

Figure 2c: Proportion of Commuters in Perimeter in Treatment 1

Figure 2d: Proportion of Commuters in Perimeter in Treatment 2

Figure 3: Commuters' Choice in the Afternoon Treatment 1, by Period

Figure 3a: Proportion of Sessions With All Commuters in Downtown in Treatment 1

Figure 3b: Proportion of Sessions With All Commuters in Perimeter in Treatment 1

Figure 3c: Proportion of Commuters Downtown in Treatment 1

Figure 3d: Proportion of Commuters Perimeter in Treatment 1
Figure 4: Commuters' Choice in the Afternoon
Treatment 2, by Period

Figure 4a: Proportion of Sessions With All Commuters in Downtown in Treatment 2

Figure 4b: Proportion of Sessions With All Commuters in Perimeter in Treatment 2

Figure 4c: Proportion of Commuters DownTown in Treatment 2

Figure 4d: Proportion of Commuters Perimeter in Treatment 2

Figure 5: Merchant Choice in the Afternoon
Treatment 1

Figure 5a: Proportion of Sessions With Both Merchants in Downtown in Treatment 1

Figure 5b: Proportion of Sessions With Both Merchants on Perimeter in Treatment 1

Figure 5c: Percentage of Merchants in DownTown in Treatment 1

Figure 5d: Percentage of Merchants on Perimeter in Treatment 1
Figure 6: Merchant Choice in the Afternoon Treatment 2

Figure 6a: Proportion of Sessions With Both Merchants in Downtown in Treatment 2

Figure 6b: Proportion of Sessions With Both Merchants on Perimeter in Treatment 2

Figure 6c: Percentage of Merchants in Downtown in Treatment 2

Figure 6d: Percentage of Merchants on Perimeter in Treatment 2