Should I Stay or Should I Go?

Equilibrium Selection in a Transportation Network

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Abstract

When imposing congestion pricing in a transportation network, especially around downtown commercial centers, there is a concern that commercial activities will have to consider relocating. Such relocations can be both risky and costly. We design an experimental game where merchants make location choices before drivers, who are the customers, make their route choices. We implement two treatments that differ in the history of experienced with congestion pricing. In each treatment players interact during an initial 10 periods with different dominant strategy equilibria caused by different congestion charges. After this initial play they interact in the multiple equilibria condition, with intermediate congestion charges, where merchants are indifferent between the possible outcomes. Payoffs are non-linear and not completely transparent, making it less than obvious that the efficient equilibrium will be selected. Our hypothesis is that selection instead is determined by simple decision rules that are influenced by history. We find that players react to the direction of change in the congestion charge: increasing the toll immediately moves traffic away from the tolled route and decreasing the toll immediately moves traffic towards the tolled route. Our findings have policy consequences since even if such route choice changes are temporary they can imply large costs to commercial activities.

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1. Introduction

When imposing congestion pricing in a transportation network, especially around downtown commercial centers, there is a 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 downtown areas we design an interactive experiment involving two types of players: merchants and driving commuters. We model a level of toll charges that implies multiple equilibria and observe if players select the efficient equilibrium or if they follow simple decision rules that do not select the efficient equilibrium. Payoffs are non-linear and not completely transparent, making it less than obvious that the efficient equilibrium will be selected and that players may rely on simple decision rules. We hypothesize that such simple decision rules may rely on the history of play prior to the toll change. We implement two treatments that differ in the history of experiences with toll charges to test the effects on equilibrium selection. Behavioral effects of history have been demonstrated in Johnson, Rutström, and George (2006) in a negative externality game and in Cooper and Van Huyck (2016) in a coordination game. Jiao (2016) shows that experiences of gains from certain actions can induce more optimism regarding the success of such actions in the future. 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, merchants are indifferent between the locations, conditional on commuters following, and commuters are always better off following merchants.

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. We investigate equilibrium selection as a function of prior experiences with different price levels, thus modeling the reactions to introductions of toll charges or to corrections in toll charges.

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 ½ due to the charges. 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, but none of these have looked at effects on commercial activities or effects on interactions between different types of players. Using an individual choice experiment 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 experiment 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 exogenous congestion pricing. Average congestion is significantly reduced but not its variability. Introducing information about other players' entry decisions in real time reduces variability significantly.

Our two treatment conditions involve creating different histories before engaging in the same multiple equilibria game. In one history treatment, players experience the traffic network without any toll charges. This history condition has a dominant strategy equilibrium with all drivers taking the downtown route. In the other history treatment, players experience the traffic network with a higher toll charge. This history condition has a dominant strategy equilibrium with all drivers taking a perimeter route, avoiding downtown. Our selection hypotheses are motivated by the possibility that, due to the non-transparent payoffs and to strategic uncertainty introduced by a large number of players, agents use low sophistication reasoning and pay limited attention to details, leading to adoptions of simple decision rules. While one equilibrium is more efficient, it is not likely that players can immediately identify this. Our main hypothesis, which motivated our design, is that players in both histories are biased in favor of past actions. Several alternative hypotheses are possible: commuters may simply react to the presence or absence of the toll, and avoid routes that are tolled, or since merchants are indifferent between equilibria these may simply choose location randomly with commuters simply following.

Based on our experimental data we reject that players simply continue historic actions, but they do react to the direction of change in the toll, which is also history dependent: increasing the toll immediately moves traffic away from the tolled route and decreasing the toll immediately moves traffic towards the tolled route. We do not find support for the alternative hypotheses that commuters simply are averse to tolled routes or that merchants make choices randomly based on their indifference over the outcomes. From a policy perspective, the observed sensitivity to the direction of the change in tolls can result in large economic costs due to the time and resources that are required to reinvest in new commercial locations.

The paper is organized as follows. The next section describes 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 sequential network game with merchants moving first, followed by commuting drivers. It was carried out using z-Tree.[1] The network is shown in Figure 1. The design is motivated by a focus on initial reactions to changes in toll charges, but we repeat each game over ten rounds so that participants can become familiar with the game. From a traffic policy perspective a one-shot setting is more natural, but the repetition allows us to observe play as payoffs become increasingly understood. The drawback of the repeated design is that it may introduce opportunities to influence the outcome of the game over time by playing out-of-equilibrium actions. However, as we will see later, we find only limited instances of such play.

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.[2] Half of the commuters start the game from a north network location (suburb), with the goal of commuting to the south to work

[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.

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 toll charge of passing through downtown for commuters. The charges are $0, $3, and $4, respectively. There are two treatment conditions: treatment 1 consists of ten rounds with a $0 charge, followed by another ten rounds with a $3 charge. Treatment 2 consists of ten rounds with a $4 charge, followed by another ten rounds with a $3 charge. The first ten rounds generate the history 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. The $3 charge is motivated by the desire to generate a common condition with multiple equilibria.

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.[3] If a merchant is located on the southbound perimeter it is the south commuters that can shop. 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 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.[4] In the downtown the maximum profit is $4 when the other merchant chooses the perimeter but all commuters go through downtown.[5]

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 on what other drivers are doing.[6] These travel times were generated in advance using the Vissim traffic simulator in order to

[3] 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.

[4] In the sessions with 6 commuters the maximum profit on the perimeter is slightly higher, $2.25, but this does not affect the equilibrium predictions.

[5] In the sessions with 6 commuters the maximum profit in downtown is $4.50, again slightly higher but not affecting the equilibrium predictions.

[6] 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.

create conditions that are consistent with actually occurring traffic.[7] 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.[8] 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 largest saving in travel time cost from taking the downtown route is $2.03. The difference in travel time on each route due to congestion generated by the other commuters is shown in the last column of the table. While these differences seem clear in this Table, it is important to note that information was not presented like this in the instructions to the participants. They were simply given a table showing the travel times on the routes conditional on the number of commuters.[9]

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

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

where *w* is the wage of $3, s_i is the shopping value conditional on *i*={inferior perimeter, inferior downtown, superior}, c_t is the charge conditional on treatment *t*={$0, $3, $4}, and τ_p^{AM} and τ_p^{PM} are the travel time costs in the morning and the afternoon, depending on route *R*={northbound perimeter,

[7] PTV Vissim at http://ptvgroup.com. The simulation software is reviewed in Fellendorf and Vortisch (2010).

[8] 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.

[9] The table with travel times given to participants is reproduced on the last page of online Appendix B, which can be found at https://cear.gsu.edu/ as wp2020-17.

southbound perimeter, downtown} and how many other commuters are on the same route at that time, with *j* indexing each drive event. [10]

2.2 *Predictions*

We make predictions for the commuter subgame first, separately for each level of charges for entering the downtown. 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.[11] The highest additional travel time cost on the perimeter is $2.03, which is less than the $3 toll. 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*:

(2) $\pi_{p,j} > \pi_{dt,j}$

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

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

Rearranging the terms we get

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

The second term of the LHS in eq. (4) 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 toll charge is required in order for commuters to select the perimeter route. Table 2 shows afternoon payoffs conditional on all commuters making the same route choices, separately for when both merchants are on the perimeter and when both merchants are in downtown. Merchant location affects only the shopping values, while route choices affect all payoff parameters except the wage. The last three rows of the table show the payoffs to the commuters

[10] Instructions given to participants are reproduced in online appendix B which can be found at https://cear.gsu.edu/ as wp2020-17.

[11] 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/ as wp2020-17.

across our three toll charges. Three asterisks indicate the best responses to merchant locations conditioned on the toll charges.[12]

On the last row of the table we can see that when the toll 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. This is the three asterisks in columns 2 and 4.. Similarly, when the toll charge is low enough, as in our $0 case on the third row from the bottom, 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. This is the three asterisks in columns 3 and 5. Because the predictions in the $0 and $4 cases are so different they generate very different histories for commuters before they enter the $3 multiple equilibria condition.

The predictions for merchants are easy for the cases with the $0 and $4 toll charges, since the dominant strategies of the commuters imply that merchants will locate on the dominant route. Table 3 summarizes the commuter predictions, conditional on merchant locations and tolls for both morning (AM) and afternoon (PM) commutes. Equilibrium predictions are shown by three asterisks for each of the three toll cases. For the $0 case the equilibrium is shown on the last row of column 3. For the $4 case the equilibrium is shown on row 3 in the last column.

The predictions for the $3 case are shown on the row labelled "Earnings if $3 toll" in Table 2. When all merchants are on the perimeter the best response by commuters is to take the perimeter, as shown by the three asterisks in column 2. When all merchants are in downtown the best response by commuters is to go through downtown, as shown by the three asterisks in column 5. All outcomes result in the same sales and profits so the merchants are completely indifferent between the location choices, since any choice they make will generate a subgame with dominant strategies for all commuters. Thus, there is an infinite number of equilibria which can result in any of the four outcomes. The outcomes that are associated with these equilibria are shown with three asterisks on all three rows in column 5 of Table 3. When one merchant is in downtown and the other on the perimeter, half of the commuters will follow to downtown and the other half will follow to the perimeter. The $3 charge leads to multiple equilibria, and we hypothesize that the equilibrium selection will depend on prior experiences that come from participating in a dominant strategy game first.

The purpose of creating a history in the game is to test if particular experiences affect the equilibrium selection in the multiple equilibria game. The expectation that simple decision rules may generate the equilibrium selection is motivated by our intentionally designed non-transparent and non-linear payoffs, and by the strategic uncertainty generated by the large number of players. Our main hypothesis is that merchants and commuters in both treatments would be biased in favor of continuing

[12] Details on payoffs conditional on north vs. south commuter, as well as the distribution of commuters across routes and the merchant locations are shown in Tables A4 – A12 in online Appendix A, which is available at https://cear.gsu.edu/ as wp2020-17.

the play from the prior condition. Jiao (2016) show that experiences of gains from certain actions can induce more optimism regarding the success of such actions in the future. Continued play could also be a result of choice inertia. We would reject this hypothesis if players in one or both treatments do not continue play from the initial conditions. Alternatively, the presence of a toll can create an aversion to taking that route. We would reject that hypothesis if players in treatment 2 choose the downtown route. Further, the change in the toll may trigger a renewed attention to the link between route choices and payoffs, perhaps even a desire to experiment with something new, and lead to a complete change in their strategies. We would reject this hypothesis if players in one or both treatments do not switch route but continue from the initial condition. Finally, given their indifference, merchants may simply choose randomly, resulting in play becoming evenly distributed across outcomes. We would then 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. Of course, it is also possible that players choose the more efficient equilibrium, although we think that the non-transparent payoffs will make this less likely.

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.[13]

3. Results

3.1 *Results from morning drives without shopping*

While the afternoon drives are of most interest due to the influence of merchant locations, 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

[13] 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.

downtown route. Figure 2a shows that there are no sessions in which all commuters take the perimeter route in any of the first ten periods, and Figure 2c shows that the proportion of commuters on the perimeter route is small and decreasing across the first ten periods.[14] 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. We conclude that the observations on morning commuters during the first 10 periods support the equilibrium predictions.

Of more interest is the observations on how the route choices are affected by the toll change. The last 10 periods in all Figures 2a-d show the \$3 charge and, because there is no shopping in the mornings, the perimeter is the predicted route.

In Figure 2c we see a dramatic change and an immediate attraction to the perimeter in period 11 with 90% of the commuters choosing that route, despite just having experienced the downtown equilibrium. We see no such dramatic change in treatment 2. Figure 2d shows only a slight drop in perimeter choices in period 11, and it is not significantly different from period 10.[15] The proportion of perimeter choices quickly returns to and exceeds the levels of the earlier periods. We conclude that morning commuters, who are not motivated by shopping values and thus are independent of merchant locations, behave in predicted ways based on the toll charges and travel costs that they face. Comparing treatments 1 and 2 we see a slightly smaller proportion of perimeter choices in the former, but the overall picture is supportive of the equilibrium prediction. While the influence from prior experiences is present in treatment 1, it is very weak.[16]

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 and payoffs therefore depend on merchant locations. 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.

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[14] The perimeter route attracts only 26% of the commuters in period 1 and 11% on average across all periods.

[15] The p-value of a Wilcoxon Signed Rank test is 0.15.

[16] More detailed discussions of results can be found in online Appendix A, which can be found at https://cear.gsu.edu as wp2020-17.

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 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. Our hypothesis is that choices will be affected by the history of experiences during the first periods.

In treatment 1 (Figure 3) we see a dramatic change from the downtown to the perimeter immediately following the imposition of the toll. Figure 3b shows a dramatic increase in the proportion of sessions where all commuters take the perimeter route, and Figure 3d show an equally dramatic increase in the proportion of drivers that take the perimeter route. These effects are strongly significant.[17] The effects are very similar to what we saw in Figures 2a and 2c for the morning drives, and we can reject the main hypothesis that drivers are simply continuing the route choices they made before the toll change. Obviously, they pay attention to the toll change and it affects their choices. The merchants also make dramatic changes in their location choices immediately after the toll imposition, as can be seen in Figure 5, despite being completely indifferent as long as they expect drivers to follow. This is strong evidence against our main hypothesis of history dependence.

In treatment 2 (Figure 4) we do see a drop in the proportion of sessions with all drivers on the perimeter in period 11, from 100% to about 43%, immediately after the toll change. However, the drop in the overall proportion of drivers on the perimeter is much weaker: from 100% to about 81%, but this change is still significant.[18] The pattern of choices in the afternoon are very similar to those in the morning, although the immediate drop in period 11 is stronger in the afternoon. We also see this drop for merchants in Figure 6. However, within only 3 periods both merchants and drivers have returned to the perimeter so this experimentation phase is short lived.

We reject our main history hypothesis that players are using a simple decision rule where they simply continue their actions from the first part of the experiment. We also reject the hypothesis that

[17] The p-value of a Wilcoxon Signed Rank test is 0001.

[18] The p-value of a Wilcoxon Signed Rank test is .0007. There is an immediate increase again in period 12 to 92%, but this increase is less significant with a p-value of 0.014.

players are simply averse to the route that is tolled, since we see a shift to downtown in treatment 2. In addition, we do not find support for the hypothesis that merchants simply choose randomly after the toll change.[19] We reject the likelihood that both merchants are on the perimeter or in downtown at the same time being 0.5. We also reject that the expected number of merchants in either of these two locations is 1.

What we do observe is an immediate reaction to the toll change in period 11, which is conditional on the different histories. In treatment 1 we have an increase in the toll and players immediately increase their use of the perimeter route. In treatment 2 we have a decrease in the toll and players immediately decrease their use of the perimeter route. The latter is in fact a move away from the efficient equilibrium.

Two things stand out from our results. First, play in the afternoon is similar to play in the mornings, with the exception that the shift to downtown in treatment 2 is not significant in the morning. Thus, one might think that the afternoon play is simply copying morning route choices due to the greater non-transparency in afternoon payoffs. However, while commuters are aware of merchant locations already when they make their morning route choices, merchants are not aware of the commuters' morning choices when making their location decisions, so this could not explain merchant behavior. Our second observation is that since merchants are the ones moving first they, and not the commuters, are the ones driving the period 11 effects: the dramatic change in treatment 1 and the weaker change in treatment 2.

Let us briefly reflect on the fact that merchants are leading the period 11 effects. Merchants switching to the downtown location in treatment 2 is consistent with them perceiving the decrease in the toll as increasing commuter earnings in downtown and either holding fairness preferences or strategically recognizing that commuters may no longer follow them to the perimeter. 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. 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. Since our game is repeated, there are opportunities for players to signal. 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 will the 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

[19] We reject the merchant hypothesis of random choice for all periods in both treatments.

Heijden (2007), Potters, Sefton and Vesterlund (2007)). In our multiple equilibria game, the perimeter is the efficient equilibrium. This can be seen in Table 4, which shows the payoffs to north and south commuters based on the assumption that merchants perfectly anticipate their choices. Since merchants are indifferent between the equilibria, commuter payoffs determine efficiency. Payoffs to both types of commuters are highest on the perimeter.

To look at the possibility of signaling we investigate behavior after period 10. In treatment 1, after the drastic drop in the selection of downtown in period 11, merchants return somewhat to downtown in period 12-14, but this trend is ultimately abandoned in period 15 and beyond (Figure 5c). Figures 3c and 3d show that while there is an increase in the commuter propensity to follow merchants back 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 times when a commuter takes the perimeter without there being a merchant there. This is equivalent to 7% of all commuter choices in the last 10 periods of treatment 1. The average earnings across those instances is -\$0.44, 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 (1.4% of observed choices). The proportions on the perimeter and in downtown are not significantly different[20], but this still suggest that in a larger study one might still see evidence of signaling. The cost to these deviating commuters is on average \$1.73, the foregone earnings of not following the merchant to downtown plus the additional travel time cost of taking the longer perimeter route. As can be seen in Table 3, the gain to commuters of moving the game to the perimeter equilibrium compared to the downtown equilibrium is \$1.72 so the cost of these deviations can be almost be fully recovered in just one period of perimeter play.

We conclude that initial play may be influenced by low sophistication reasoning, but it is possible that subsequent play is influenced by payoff experiences.

4. Summary and Conclusions

We design and implement an experiment with a sequential game between merchants and commuters to investigate responses to changes in toll charges. From the perspective of policy it is important to consider that if toll charges are effective at moving traffic out of congested downtown commercial centers then merchants that remain would lose sales and earnings. On the other hand, merchants that move based on erroneous expectations of traffic changes would also lose sales and earnings. 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. Compared to experimental testing of game theoretic models where the payoff consequences of

[20] The p-value in a one-sided Fishers exact test is 0.63.

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, however 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 in this experiment than in experiments with simple payoff matrices. Additionally, there are more than two commuters in the game 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 and the initial 10 periods generate the different histories based on dominant strategies. In our non-transparent payoff setting it is possible that players use low sophistication reasoning and pay limited attention to details, leading to adoptions of simple decision rules.

Our main hypothesis is that commuters will continue their action choices from the history part of the game, and that merchants anticipate this. While we do not find support for this, we do find that history matters in a different way: commuters react to the *direction* of change in the toll, which differs with the history treatments. An increase in the toll leads to an immediate reallocation away from the tolled route but a decrease leads to an immediate reallocation towards the tolled route. Since the game is repeated we eventually see players approach the efficient equilibrium. During the adjustment periods we see some evidence of costly signaling from commuters, who are the ones benefitting from the efficient equilibrium. Even though the initial reaction to the toll change is temporary, such increases in demand on non-equilibrium routes can lead merchants to make costly relocation investments that later have to be abandoned.

What are the implications for traffic planning from these findings? The good news first: the introduction of a toll that leads to multiple equilibria and therefore a selection problem has a good chance of eventually moving the traffic system into the efficient equilibrium even when payoff consequences are not fully transparent. In both of our treatments we saw that the efficient equilibrium, the perimeter, attracted a large share of players. However, the bad news is that there is also a real risk for costly misallocations of merchant activities immediately following a reduction in tolls from a higher level. Treatment 2 shows that merchants mistakenly move to the inefficient downtown location, and commuters follow and it then takes several periods for play to return to the perimeter. In the field such dynamics can be very costly due to the time and resources that are required for reallocating commercial investments. On the other hand, introducing a toll into a previously un-tolled traffic system, as in treatment 1, can lead to a very quick move to the efficient equilibrium.

The reaction to the reduction in the toll in treatment 2 is reminiscent of behavior we see in queues. Whether you are in a queue to the cash register in a busy grocery store, or queueing up on the freeway during rush hour traffic many people tend to overestimate the gains they can make by moving to another queue that appears to be moving faster, and subsequently attempt to return to the original queue.

Due to the observed move away from the efficient equilibrium in treatment 2 we think toll authorities would be wise to be cautious when introducing tolls, and to start with lower levels that may subsequently be increased if the initial levels do not result in the desired changes in traffic flows. If the initial toll turns out to be too high, later downward adjustments can lead to costly misallocations of commercial activities.

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Figure 1: The Network

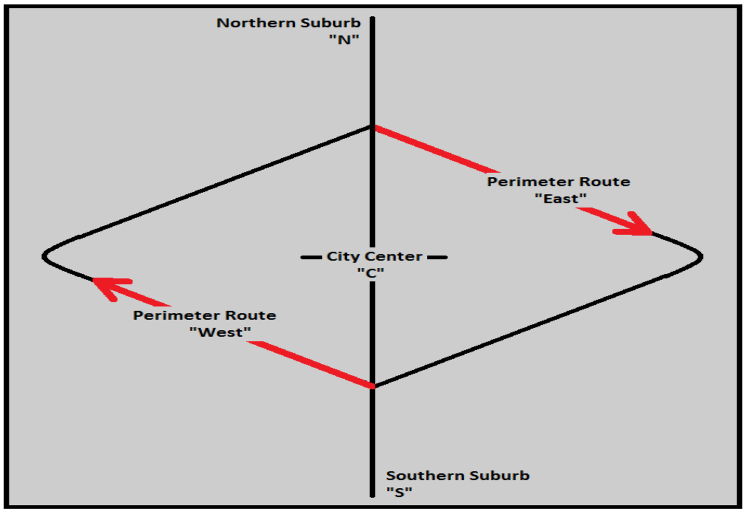


Table 1: Travel Time Costs

	All other drivers take downtown	All other drivers take perimeter	Difference due to congestion on the route
Southbound downtown	$1.15	$0.95	$0.20
Northbound downtown	$1.25	$1.00	$0.25
Southbound perimeter	$2.35	$2.50	-$0.15
Northbound perimeter	$2.66	$3.03	-$0.37
Southbound difference	$1.20	$1.65	
Northbound difference	$1.41	$2.03	

Table 2: Commuter Payoffs and Afternoon Predictions

	All on Perimeter Route	All on Downtown Route	All on Perimeter Route	All on Downtown Route
	Merchants on Perimeter		Merchants in Downtown	
Wage	$3	$3	$3	$3
Shopping value	$4	$3	$2	$4
Travel time cost	-$3.03	-$1.25	-$3.03	-$1.25
Earnings if $0 toll	$3.97	$4.75***	$1.97	$5.25***
Earnings if $3 toll	$3.97***	$1.75	$1.97	$2.25***
Earnings if $4 toll	$3.97***	$0.75	$1.97***	$1.25

This table shows the earnings consequences for a north commuter. The earnings for a south commuter are qualitatively similarly, but differ slightly due to different travel time costs.
*** Equilibrium Predictions

Table 3: Equilibrium Prediction Summary

Merchant location choices	**$0 toll**		**$3 toll**		**$4 toll**	
	AM	**PM**	**AM**	**PM**	**AM**	**PM**
	Commuter route choices					
Both Merchants on Perimeter	All Downtown	All Downtown	All Perimeter	All Perimeter ***	All Perimeter	All Perimeter ***
One Merchant on Perimeter and one in Downtown	All Downtown	All Downtown	All Perimeter	Half Perimeter and half Downtown ***	All Perimeter	All Perimeter
Both Merchants in Downtown	All Downtown	All Downtown ***	All Perimeter	All Downtown ***	All Perimeter	All Perimeter

The column AM shows predictions for morning commutes and the column PM shows predictions for afternoon commutes. The text in each cell shows the predicted route choices for the commuters. Merchant locations do not matter to AM commutes.
*** Equilibrium predictions in afternoons with merchants present

Table 4: Commuter Afternoon Payoffs with $3 Charge

South / North Commuters	**Downtown**	**North Perimeter**
Downtown	$2.85 / $2.75	$2.93 / $4.21
South Perimeter	$4.49 / $2.81	$4.50 / $3.97

Figure 2: Commuters' Perimeter Choice in the Morning by Period

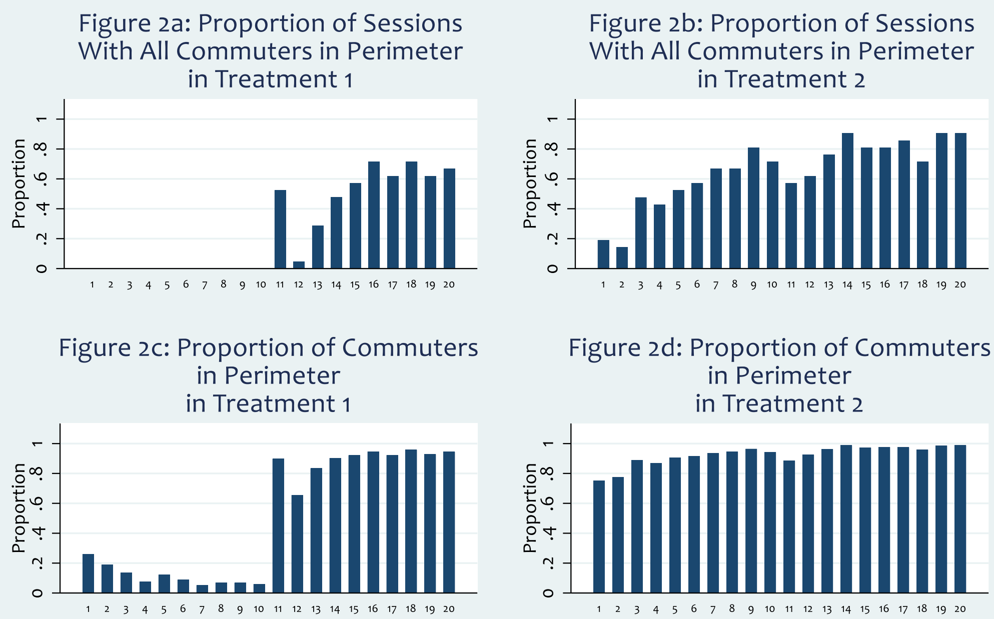
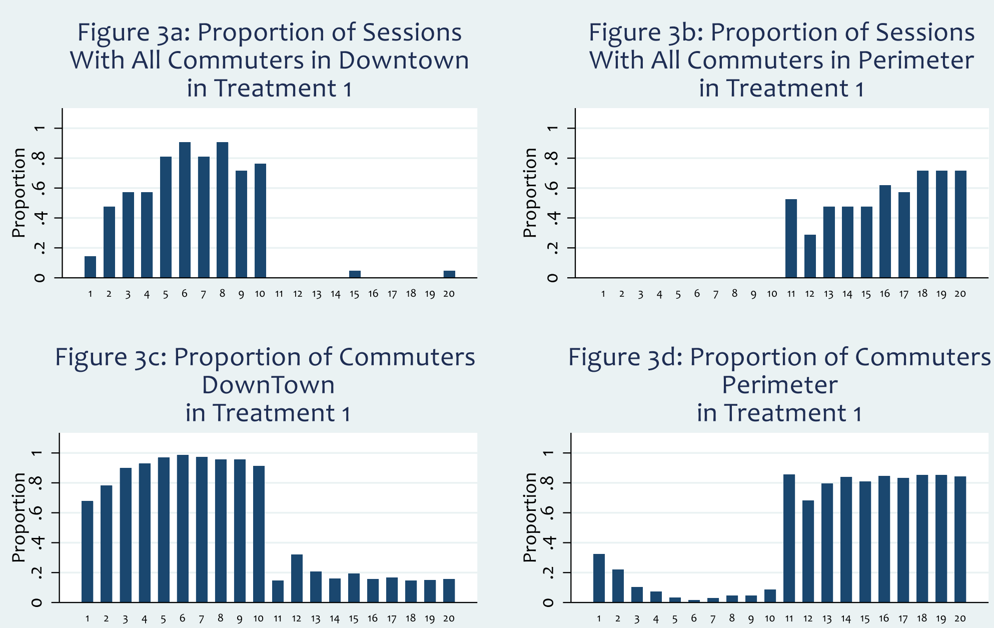


Figure 3: Commuters' Choice in the Afternoon Treatment 1, by Period



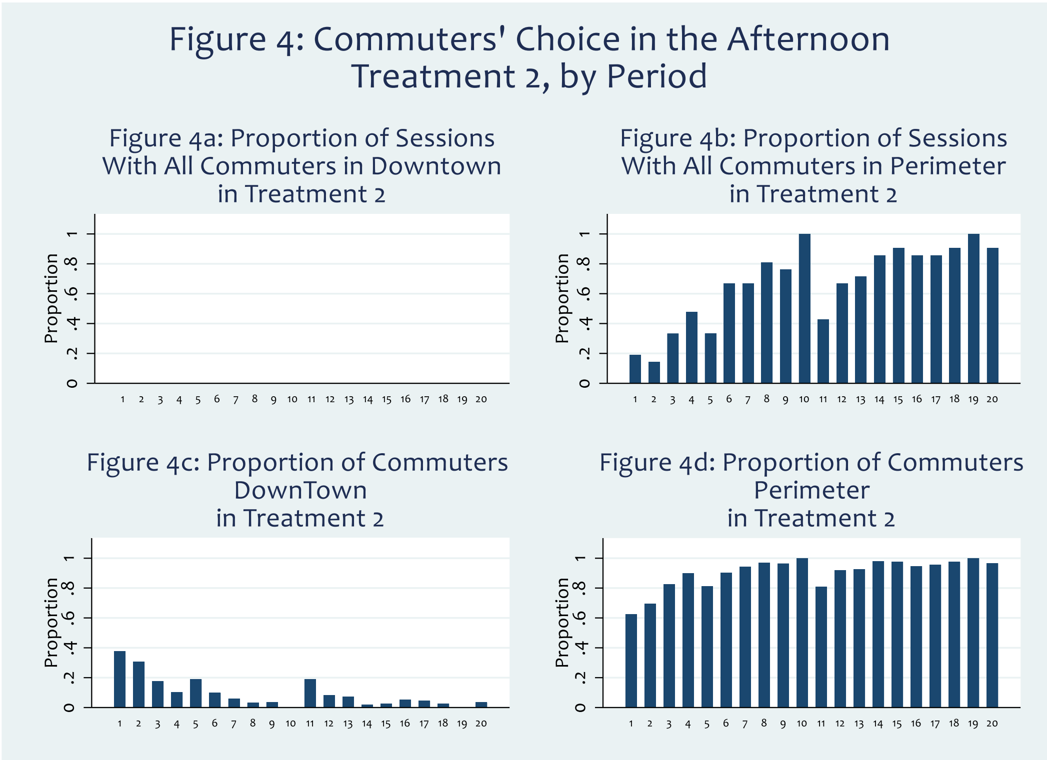


Figure 4: Commuters' Choice in the Afternoon
Treatment 2, by Period
Figure 4a: Proportion of Sessions
With All Commuters in Downtown
in Treatment 2
Figure 4b: Proportion of Sessions
With All Commuters in Perimeter
in Treatment 2
Figure 4c: Proportion of Commuters
DownTown
in Treatment 2
Figure 4d: Proportion of Commuters
Perimeter
in Treatment 2
Proportion
0 .2 .4 .6 .8 1
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20

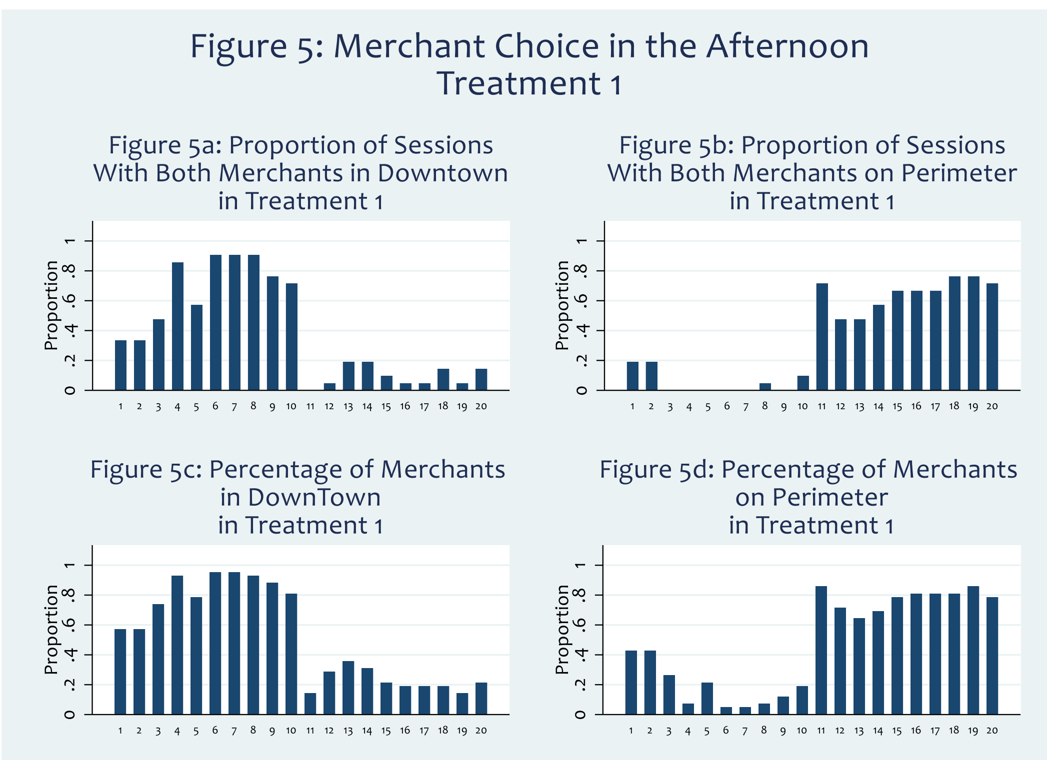


Figure 5: Merchant Choice in the Afternoon
Treatment 1
Figure 5a: Proportion of Sessions
With Both Merchants in Downtown
in Treatment 1
Figure 5b: Proportion of Sessions
With Both Merchants on Perimeter
in Treatment 1
Figure 5c: Percentage of Merchants
in DownTown
in Treatment 1
Figure 5d: Percentage of Merchants
on Perimeter
in Treatment 1
Proportion
0 .2 .4 .6 .8 1
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20

Figure 6: Merchant Choice in the Afternoon
Treatment 2