Should I Stay or Should I Go?

Congestion Pricing and Equilibrium Selection in a Transportation Network

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Abstract

When imposing traffic congestion pricing around downtown commercial centers, there is a concern that commercial activities will have to consider relocating due to reduced demand, at a cost to merchants. Concerns like these were important in the debates before the introductions of congestion charges in both London and Stockholm and influenced the final policy design choices. This study introduces a sequential experimental game to study reactions to congestion pricing in the commercial sector. In the game merchants first make location choices. Consumers, who drive to do their shopping, subsequently choose where to shop. Initial responses to the introduction of congestion pricing and equilibrium selection adjustments over time are observed. These observations are compared to responses and adjustments in a condition where congestion pricing is reduced from an initially high level. Payoffs are non-linear and non-transparent, making it less than obvious that the efficient equilibrium will be selected, and introducing possibilities that participants need to discover their preferences and anchor on past experiences. We find that initial responses reflect standard inverse price-demand relation, and that adjustments over time rely on signaling by consumers leading to the efficient equilibrium. There is also evidence that priming from initial experiences influence play somewhat. We confirm that commercial activities relocate following the introduction of congestion pricing and that the adjustment process is costly to merchants.

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

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1. Introduction

When imposing traffic congestion pricing around downtown commercial centers, there is a concern that commercial activities will have to consider relocating due to reduced demand. Concerns like these were important aspects of the debates before the introductions of congestion charges in both London and Stockholm and influenced the final policy design choices (Safirova et al. (2006), Eliasson et al. (2009)). Relocations to city perimeters can be both risky and costly since the effects of the congestion charges are uncertain, and additional changes to the charges may occur over time requiring additional relocations. City center merchants that underestimate the drop in demand and remain in the center will face sales losses, as will merchants that overestimate the drop in demand and relocate to the perimeter unnecessarily. Analyses of the experiences in London and Stockholm find no evidence that economic activities were reduced on average after the introduction of congestion charges. However, there is evidence that particular activities that rely on consumers who travel by car and who cannot shift to shopping at hours outside of charging hours were negatively affected. In London only a very small portion of consumers relied on car travel, and in Stockholm consumers were able to shift to times outside of the charging hours, but this is not the case in many other cities.

A complementary approach to analyzing field data from past implementations of congestion pricing is to use experiments. While analyzing field data is a better tool for looking at net effects in complex situations, such analyses are limited to the specific circumstances of the cases studied. Many factors influence net results, all of which are not observed so that causal factors cannot fully be inferred. Theory guided experiments can provide universally applicable insights into some causal forces that are at play. Limitations on lessons from experiments arise from the particular assumptions and parameter values that are used in the experimental design. The present experiment is focused on the effect of changes in congestion charges on merchants that interact with consumers who have to travel by car to do their shopping. This is particularly relevant for cities with more limited urban transit systems, such as many cities in the US or in some less developed countries. We are interested in the reactions to changes in congestion charges and how these reactions depend on past experiences.

We model a sequential game where merchants make location decisions first and consumers then choose where to shop. In the initial phases of the game consumers have dominant strategies that differ across treatments. In one treatment the congestion charge is relatively high and the dominant strategy is to shop outside of the congestion zone, on the perimeter. In the other treatment the congestion charge is zero and the dominant strategy is to shop in downtown. In a final phase, which is the same across treatments, the congestion charge is intermediate with multiple Nash equilibria where merchants are indifferent between the equilibria and consumers best responses are to follow the merchants. We are interested in how the merchants and shoppers react to the introduction of the congestion charge when it is initially zero, and then compare that to reactions when the charge is reduced from a higher level. One of the equilibria is for merchants to not relocate and for consumers to continue to shop from the same merchants, thus not reducing demand. Thus, despite our game being based on consumers who drive it is possible for the experiment to show no effect on retail activities from the introduction of the congestion charge.

There are several behavioral possibilities that can affect the equilibrium selection apart from remaining in the initial equilibria. One possibility is that play converges on the one equilibrium which is efficient, the perimeter one. Alternative hypotheses arise in our experiment due to payoffs being non-linear and non-transparent, generating outcomes with uncertain values. This can lead to players either constructing or discovering preferences as they play the game. In such cases Tversky and Kahneman (1974) propose that psychological anchoring behaviors can occur. If consumers anchor on past prices, as investigated by Sitzia and Zizzo (2012), it can lead to reduced demand adjustments following a price change, such that for any given final price a higher quantity demanded will result when consumers have previously experienced higher price than when they have experienced lower prices. Consumers' perception of the value of the good is influenced by past prices. Anchoring behavior seems particularly prevalent when consumers have unclear preferences or perceive a product as having an uncertain value (Sitzia and Zizzo (2012)). In such cases the revealed preferences would be quite sensitive to the framing of the task (Slovic and Lichtenstein (1983)) or to priming from past experiences, even when the past situation is no longer relevant (Ariely, Loewenstein, and Prelec (2003)). Cooper and Stockman (2011) find evidence that experimental participants are discovering their preferences and that these are influenced by priming in a prior task.

Our observations lead us to reject that merchants choose locations randomly despite being indifferent between equilibria, and to reject that merchants do not relocate after the charge is imposed. Most of the consumer decisions are to follow merchants. Our findings show that immediate reactions to the change in congestion charges follow a standard inverse price-demand relationship. When the price of entering downtown increases it reduces commercial activities in downtown and when the price of entering downtown decreases it increases commercial activities in downtown. The reaction is quite strong in our main treatment with increasing price. The fact that merchants react to the price is interesting since merchants are indifferent between staying in the initial equilibrium or changing to a new equilibrium, and consumers' best responses are to follow the merchants. We do see dynamic behavior that leads to a convergence on the efficient perimeter equilibrium in the second phase of both treatments. Consumers are signaling their preferences for the perimeter location, and merchants respond to those signals.

The adjustment process that is caused by the change in the congestion charge is costly to merchants, consistent with the concerns expressed in the debates about congestion pricing. We do not find any systematic evidence of price anchoring, where consumers valuations are influenced by past prices, as in Sitzia and Zizzo (2012)). Such anchoring would be expected to increase activities inside the congestion charging zone in the treatment where price is decreasing relative to the treatment where price is increasing. Instead, we see the opposite, a higher proportion of activities inside the congestion charging zone in the treatment with a price increase. In this treatment players have prior experience with a dominant strategy equilibrium inside the charging zone. This finding is consistent with a portion of our players being influenced by priming: the unique downtown equilibrium in the first phase of the game has a lingering influence on equilibrium selection in the second phase of the game.

1.1 Field evidence

Since Singapore introduced congestion charging zones in 1998, several other cities have followed: London in 2003, Stockholm in 2006, Milan in 2008, Bergen in 2016 and Oslo in 2017. The charging schemes in London and Stockholm have been well analyzed. London introduced a £5 cordon charge in February 2003 with an increase in the rate charged to £8 in July 2005 £8. The charging window was set to 7 am until 6.30 pm. The effect on traffic after the initial cordon was put in place was an 18% reduction and no evidence of increases in traffic outside of the charging hours or in the area immediately surrounding the charging zone. There was no sign that this effect weakened over the following years (Transport for London (2006)). Stockholm introduced a 6 month trial period of congestion charging around the city center in 2006, followed by a permanent installation in 2007. There are three charging windows with differentiated rates, plus periods with no charge. The charges were initially set to achieve a 15% reduction in the traffic volume but the result was a full 22% reduction which has been sustained in the long run. A temporary removal of the charge system after the 6 month trial quickly returned traffic to close to previous levels, showing how quickly traffic flows can change. Both average travel times and the dispersion of travel times were reduced by 1/3 to ½ due to the charges. (Eliasson et al. (2009), Eliasson (2014)). This demonstrates that congestion charges can be effective ways of reducing congestion in downtown areas.

In both London and Stockholm prior to the introduction of congestion charging there were expressed concerns about possible detrimental effects on the commercial sector, and especially the retail sector, in the city centers. Subsequent analyses ex post of introducing the charging show no, or little, evidence of net effects on the economy as a whole or on the retail sector as a whole (Transport of London (2006), Quddus, Carmel, and Bell (2007a, 2007b), Daunfeldt, Rudholm and Rämme (2009, 2013)). However, these net effects are a result not only of the congestion charges themselves, but also of a set of complementary policies improving public transit as well as larger social and economic changes during the same time. The lack of effects in London is likely associated with the very small proportion of shoppers in the city center who travel there by car. Quddus, Carmel, and Bell (2007a, 2007b) report that only 3-6% of shoppers in London travel by car. The lack of effects in Stockholm is likely associated with the longer opening hours of downtown stores allowing car-borne shoppers to do so outside of charging hours (Daunfeldt, Rudholm and Rämme (2009, 2013). In addition, the expressed concerns about effects on the retail sector directly affected the design of the congestion charges so as to minimize any such effects. Nevertheless, a few pieces of evidence speaks to a direct effect of congestion charges on retail in city centers: a significant decrease in sales for a particular store in central London which has a high proportion of shoppers who travel by car (Quddus, Carmel, and Bell (2007a, 2007b)), and a 17% drop in travel for shopping purposes to central Stockholm during the trial portion of the congestion charging (Smidfeldt-Rosqvist et al. (2006)). That this reduction in Stockholm did not affect retail revenues in a significant way could be due to the fact that opening hours extend well beyond the congestion charging range. Further evidence of negative effects on retail is found in Singapore which experienced a 19% drop in retail real estate prices within the charging zones relative to outside of these zones (Agarwal, Koo and Sing (2015)).

Our experimental findings that, in cities where consumers travel by car, there are behavioral forces that cause shifts of commercial activities and adjustments over time, complement and add to this evidence. 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, section 4 relates to the experimental literature and section 5 concludes.

2. The experimental game

2.1 *Design*

The experiment consists of a sequential network game with two merchants moving first, followed by 6 or 8 driving consumers. 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 congestion charges, but we repeat each game over ten rounds so that participants can gain experience. From the perspective of traffic policy a one-shot setting is more natural, but the repetition allows us to observe play as payoffs become increasingly understood. This repeated design also allows us to investigate whether and how adjustments take place over time and how this influences equilibrium selection.

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 are randomly assigned to one of them after making the perimeter choice. There are either 6 or 8 consumers, the numbers vary across sessions.[2] Half of the consumers start the game from a north network location (suburb), with the goal of traveling to the south to work in the morning and then travel back north to home in the afternoon, stopping for shopping on the way. The other half of the consumers start from a south location with the reverse travel directions. The downtown route is two-way so both north and south commuters 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. Northbound travel take place on the west side of the perimeter while southbound travel takes places on the east side of the perimeter.

The experiment is conducted under three conditions, varying the congestion charge of passing through downtown for consumers. The charges are $0, $3, and $4, respectively. There are two treatment conditions: treatment 1 consists of a phase one with ten rounds with a $0 charge, followed by

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[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.

a phase two with another ten rounds with a $3 charge. Treatment 2 consists of a phase one with ten rounds with a $4 charge, followed by a phase two with another ten rounds with a $3 charge. The first phases of the treatments generate the history that is hypothesized to influence behavior in the $3 charge condition, for example if consumers are anchoring on past prices. 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 intent of generating a common condition with multiple equilibria. While our main interest is in treatment 1, treatment 2 serves as a control condition that allows us to assess whether the behavioral factors we infer are general and not specific to the temporal ordering of treatment 1.

The game is sequential with merchants moving first and consumers following. This is motivated by the assumption that merchants cannot relocate as quickly as consumers can shift shopping location and thus cannot wait to first observe what consumers are doing. Merchants who do not correctly anticipate consumer choices will suffer a loss in sales.

Merchants make profits by selling to consumers who pass them by during the afternoon. In the sessions with 8 consumers a merchant makes a 50 cent profit for each consumer that shops from him.[3] If a merchant is located on the southbound (east) perimeter it is the south consumers that can shop. If the merchant is located on the northbound (west) perimeter his shoppers are the north consumers. If the merchant is located in downtown both north and south consumers can shop. However, if both merchants are in downtown they will share demand equally. Shoppers cannot choose which merchant they shop from if both are in downtown and all consumers must shop during the afternoon commute. The maximum profit for a merchant on the perimeter is $2.[4] In downtown the maximum profit is $4 when the other merchant chooses the perimeter but all consumers go through downtown.[5]

Consumers receive a $3 endowment in each period, referred to as a wage. When they shop on their return travel 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 human 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.[6] Consumers incur a travel cost both in the morning and in the evening. For each second they travel they are charged 1 cent. Table 1 shows how travel times are affected by the consumer's route choice conditional on

[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] These parameters were selected, together with the congestion charge, to generate the intended equilibria. If the human merchants had not been modeled with superior shopping values there would have been no incentives for consumers to care about merchant locations.

what other consumers are doing.[7] These travel times were generated in advance using the Vissim traffic simulator in order to create conditions that are consistent with actually occurring traffic.[8] 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.[9] 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 travel choices of the other consumers, 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 consumers 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 each of the two routes conditional on the number of commuters.[10]

Finally, if consumers travel through downtown they have to pay the charge, with the amount depending on what condition they are in. The consumer earnings, for each consumer j, can therefore be specified as:

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

[7] 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.

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

[9] 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 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.

[10] 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 wp2021-08.

where w is the wage of \$3, $s_{i,j}$ is the shopping value conditional on i={inferior perimeter, inferior downtown, superior}, $c_{t,j}$ is the charge conditional on treatment t={\$0, \$3, \$4}, and $\tau_{R,j}^{AM}$ and $\tau_{R,j}^{PM}$ are the travel time costs in the morning and the afternoon, depending on route R={northbound perimeter, southbound perimeter, downtown} and how many other consumers travel on the same route at that time.[11]

Due to the non-linear nature of the travel times and the fact that consumers need to do their own calculations of the net payoffs, rather than the instructions giving them transparent complete payoff profiles, consumers will require some experience to understand their best responses. All players are given common information about payoff parameters that stay constant throughout the game, such as shopping values, toll charges, and the summary of possible travel times. Actual travel times, however, are endogenous and vary across routes. Feedback about actual outcomes and payoffs are given privately, implying that information becomes asymmetric over time. This makes it difficult for merchants to correctly anticipate consumer responses to their location choices. In phase 1 merchants may not immediately realize that consumers have dominant strategies and in phase 2 consumers may not immediately understand that their best response is to follow the merchants.

2.2 *Predictions*

We make predictions for the consumer 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.[12] The highest additional travel time cost on the perimeter is \$2.03, which is less than the \$3 charge. Thus, we focus here on the predictions for the afternoon commutes when shopping occurs.

In the afternoon, the predictions for consumers depend on the relative earnings of the two routes. The condition for choosing the perimeter is that, for each consumer 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

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[11] Instructions given to participants are reproduced in online appendix B which can be found at https://cear.gsu.edu/ as wp2021-08.

[12] The implied payoffs for north- or southbound travel in the mornings is shown in Tables A1 and A2 in Appendix A, available at https://cear.gsu.edu/ as wp2021-08.

(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; consumers 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 congestion charge is required in order for consumers to select the perimeter route. Table 2 shows afternoon payoffs and best responses to merchant locations. Merchant locations affect consumers' shopping values only, while route choices affect all consumer payoff parameters except the wage. The last three rows of the table show the payoffs to the consumers across our three charges. Three asterisks indicate the consumers' best responses to merchant locations conditioned on the congestion charges.[13]

On the last row of the table we can see that when the congestion charge is high enough, as in our \$4 case, the consumers 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 indicated with three asterisks in columns 2 and 4. Similarly, when the charge is low enough, as in our \$0 case on the third row from the bottom, the consumers 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 indicated with three asterisks in columns 3 and 5. In the \$3 case consumer best responses are to follow the merchant. When both merchants are on the perimeter all consumers will go to the perimeter, and when both merchants are in downtown all consumers will go to downtown.

The predictions for merchants are easy for the cases with the \$0 and \$4 toll charges, since the dominant strategies of the consumers imply that merchants should locate on the dominant route. Table 3 summarizes the consumer 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 and it is determined by the dominant strategy of the consumers. For the \$4 case the equilibrium is shown on row 3 in the last column, also determined by the dominant strategy of the consumers. Since merchants move first in this sequential game they need to anticipate consumer choices. If they fail to predict that consumers have dominant strategies, which is likely since payoffs are non-transparent, they will experience periods of losses in sales revenues.

The equilibrium predictions for the \$3 case are shown in columns 4 and 5 of Table 3. All outcomes shown in this table 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 where consumers

[13] 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 wp2021-08.

should simply follow the merchants. Thus, there are four pure strategy Nash equilibria with outcomes shown by three asterisks on all three rows in column 5 of Table 3. One possible Nash equilibrium is for the merchants to stay in the locations from phase 1, implying that in treatment 1 the equilibrium would be downtown and in treatment 2 it would be the perimeter. Another possible Nash equilibrium under full information conditions is for merchants to choose location randomly. 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. Because the dominant strategy equilibria in the $0 and $4 cases are so different they result in very different experiences that may affect equilibrium selection in the $3 case.

Of the four pure strategy equilibria in the $3 case only one is efficient, the perimeter one. This can be seen in Table 4 that shows consumer payoffs across all four equilibria. The efficient perimeter equilibrium is preferred by both north and south consumers. Deviations from equilibrium predictions are likely to happen, particularly in the early periods. First, merchants may be primed by the experiences in phase 1 where consumers have dominant strategies and are not following the merchants and expect this to continue in phase 2. If so, merchants will try to anticipate consumer choices, but since payoffs are non-linear and non-transparent it is difficult for merchants to predict precisely what consumers will do. The only equilibrium that will lead to no relocation costs or lost sales revenues in this game is the one where merchants do not shift location and consumers follow them.

Because phase 2 has multiple equilibria, where one is efficient, it resembles a coordination game. However, the sequential nature of the game, the indifference of the merchants, and the best responses by consumers to follow merchants imply that there is not a coordination problem in the usual sense for the players to solve. Nevertheless, one equilibrium is strictly preferred over the others by consumers and since merchants are not averse to that equilibrium, one may think of the dynamic selection process as one similar to coordination, even though it would take place across periods.

We form the following hypotheses regarding reactions to the change in congestion charges in phase 2. If the behavioral forces are general, we should see them in both treatments 1 and 2:

H1: Merchants do not change their location decisions from phase 1.

This hypothesis is based on the fact that merchants are indifferent between outcomes and have no reason to change their actions. It relies on them believing that consumers have a best response to follow them.

H2: Merchants choose location randomly.

This hypothesis is also based on the fact that merchants are indifferent between outcomes and that they believe that consumers have a best response to follow them. Random choice is as good as any other way of making choices.

H3: Merchants expect consumers to act in a manner consistent with an inverse price-demand relationship and choose locations accordingly.

This hypothesis is based on merchants believing that consumers will not simply follow them, and therefore they have to anticipate consumer choices. Such beliefs are consistent with them having experienced phase 1 with consumers not following them due to dominant strategies. They may expect that consumers react to the price change without completely understanding the payoff consequences.

H4: Merchants expect consumers to behave according to anchoring theories and choose locations accordingly.

This hypothesis is based on merchants believing that consumers will not simply follow them, and therefore they have to anticipate consumer choices. Such beliefs are consistent with them having experienced phase 1 with consumers not following them due to dominant strategies. They may expect price anchoring behavior if they believe that consumers are influenced by past prices when forming their preferences over options with uncertain outcomes. Or they may expect consumers to have been primed by their dominant strategy experiences in phase 1 and thus have a tendency to continue such play.

H5: Consumers play their best responses which is to follow merchants.

This hypothesis is consistent with consumers understanding their payoffs despite the non-linear and non-transparent information environment.

H6: The game converges on the efficient equilibrium.

This hypothesis is consistent with consumers increasingly understanding payoffs over time as their experience grows.

H7: Consumers engage in costly signaling to influence the game in the direction of the preferred perimeter equilibrium.

This hypothesis is consistent with consumers understanding their payoffs enough to see the attraction of the perimeter equilibrium, and believing that they can influence the indifferent merchants sufficiently by generating foregone sales revenues through not following them, i.e. by signaling.

H8: Consumers anchor on past prices as if these reflect current values.

This hypothesis is consistent with price anchoring as discussed in Sitzia and Zizzo (2012) where consumers who are unclear on their preferences or who are uncertain about the values of goods anchor on past prices. If a new price of a good is reached through a price decrease, the final demand will be greater than if the same new price is reach through a price increase.

H9: Consumers behave according to anchoring theories where priming due to past experiences influence play.

This type of anchoring is discussed in Cooper and Stockman (2011). Past experiences can have an impact on behavior even when the conditions that generated those past experiences are no longer relevant.

2.3 *Experimental procedures*

The experiments were conducted in February and March 2013 in the ExCen lab at Georgia State University with student participants. There are 42 networks, half of them with 6 consumers and the other half with 8 consumers, 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.[14]

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 consumers in downtown.

Figure 2 shows the proportion of consumers who took the perimeter route in the mornings, pooled across all sessions within each treatment, by period. The only parameters that influence morning travel choices are travel times and toll charges, since there is no shopping value. Figure 2a shows treatment 1, where the first 10 periods have a $0 charge and the prediction is for all to take the downtown route. The proportion of consumers on the perimeter route is small and decreasing across the first ten periods.[15] Figure 2b shows treatment 2, where the first 10 periods have a $4 charge and where the perimeter is the predicted route. The proportion of consumers on the perimeter route starts as high as 75% in period 1 and increases steadily. We conclude that the observations on morning consumers 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 Figures 2a-d show the $3 charge and, because there is no shopping in the mornings, the perimeter is the predicted route. In Figure 2a (treatment 1) we see a dramatic change and an

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

immediate attraction to the perimeter in period 11 with 90% of the consumers choosing that route, despite just having experienced the downtown equilibrium. With the exception of Period 12, where there is a discrete drop, all the other periods have a high proportion of consumers on the perimeter and these are not significantly different from period 11.[16] 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. The proportion of perimeter choices quickly returns to and exceeds the levels of the earlier periods. We conclude that morning travelers, 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.

3.2 *Results from afternoon drives with shopping*

Our main interest is in the afternoon drives where the consumers are shopping on the way home and payoffs therefore depend on merchant locations. Figure 3 shows the proportion of consumers on each route in the afternoon, by period and treatment. Figure 3a shows the proportion of consumers in downtown in treatment 1. Figure 3b shows the same thing for treatment 2. The perimeter choices for treatment 1 are shown in Figure 3c and for treatment 2 in Figure 3d. These two figures are obviously mirror images of 3a and 3b.

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 3a) the maximum proportion of consumers in downtown is found in period 6 and is 99%. In period 1 the proportion is already 68%. In the \$4 case (Figure 3d) the maximum proportion of consumers on the perimeter is found in period 10, and it is an astounding 100%. Every single consumer takes the perimeter route.

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 equilibria. The predicted consumer route choices now depend on where the merchants locate, and the merchants themselves are indifferent, as long as they expect consumers to follow them.

As can be seen in Figure 4, merchants immediately react to the change in congestion charge so we can reject H1 that there is no effect on location choices. The reactions are consistent with the simple inverse price - demand effects of H3. Figures 4a and 4c illustrate treatment 1 and Figures 4b and 4d illustrate treatment 2. In treatment 1 where the charge increases merchants leave downtown and in treatment 2 where the charge decreases they leave the perimeter. Figure 4a shows a drop in the percentage of merchants in downtown from 80% in Period 10 to 14% in Period 11 in treatment 1.

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[16] All statistical tests are t-tests or Wilcoxon Signed Rank tests. Significance implies p-values < 0.01 The stata code that includes all our tests is uploaded with our working paper wp2021-08 to https://cear.gsu.edu/.

Figure 4d shows a drop in the percentage of merchants on the perimeter from 100% in Period 10 to 71% in Period 11 in treatment 2. These changes across periods are highly significant. The change is significantly larger in treatment 1 than in treatment 2, which is not surprising given that the charge change is also larger.[17] This is evidence that the change in the charge directly affects decisions, but in treatment 2 we see more of a reluctance to move away from the historic choices. If merchants expect consumers to act according to theories where the perceived value is anchored on past prices (as in Sitzia and Zizzo (2012)), we would see more merchants in downtown in treatment 2 than in treatment 1 during the $3 phase. The proportion of merchants in downtown in period 11 is 29% in treatment 2 and only 14% in treatment 1, but this difference is only significant at 5% level. Further, during the last 5 periods we see the opposite relationship between the treatments: the proportion of merchants in downtown in treatment 2 is only 4% whereas it is 19% in treatment 1, and this difference is significant. We conclude that our evidence in favor of H4 depends on merchants expecting consumers to be primed by their initial experiences, but not to have their value perceptions influenced by past prices.

We can interpret the immediate reaction in period 11 as an indication of what might happen in a market where merchants have very little experience with demand shifts across locations. Across periods experience is increasing and we can interpret the later location choices as reflecting merchants with a great deal of experience in demand shifts across locations. In both treatments there is a tendency for merchants to return to previous locations after period 11. In treatment 1 the percentage of merchants in downtown increases from 14% to 29% between periods 11 and 12. However, this change is not significant and the location choices are still significantly different from the 80% in period 10. Throughout the remainder of treatment 1 the perimeter keeps holding a much stronger attraction than downtown, although the latter is never abandoned completely: 19% of merchant locations are in downtown during the last 5 periods. We similarly see that merchants in treatment 2 return to the perimeter after period 11. The percentage of merchants on the perimeter increases from 71% to 83% between periods 11 and 12. While this change is not significant, during the last 5 periods 96% of the location decisions are on the perimeter and this is significantly higher than the 71% of period 11.

We can also reject H2, that merchants choose location randomly. We reject that the likelihood that both merchants are on the perimeter or in downtown at the same time is 0.25. The actual proportions are shown in Table 5 and they are all very different from 0.25 with the closest one being the 0.10 for the $3 charge in treatment 1. We also reject that the expected number of merchants in either of the two locations is 1. The observed average number of merchants in the two locations is shown in Table 6. The perimeter location is clearly favored in all conditions, with the exception of when the charge is $0.

Earnings consequences are the most salient experiences influencing merchant decisions in this game. What are the earnings consequences to merchants of the change of location in period 11? The merchants who respond to the change in charge and move to the other location are doing less well in terms of profits than they did on average during the first ten periods. In treatment 1, those who move to

[17] All tests of location choices are chi square tests.

the perimeter experience a profit loss of $0.29 in period 11 compared to the average profits they made in downtown during the last 5 periods of the $0 charge phase. While this may be seen as an incentive to return to the downtown we see a contrarian influence from the fact that those few merchants who continue to locate in downtown experience an even greater loss of $0.48. The fact that we have average losses for both locations indicate that not all consumers are following merchants, thus leaving less overall demand for the merchants. In treatment 2, those who move to downtown from the perimeter lose $0.78, providing stronger incentives to move back to the perimeter compared to treatment 1. Those who stayed on the perimeter in treatment 2 did not experience a loss in profits. As in treatment 1, the loss in downtown indicates that consumers are not always following the merchants.

We therefore turn to investigate the choices made by consumers, and in particular whether they appear to signal their location preferences by choosing the perimeter even when no merchant is there. This may be expected as the perimeter equilibrium is preferred by consumers.

In treatment 1 (Figure 3a and 3c) we see a dramatic change in consumer route choices from downtown to the perimeter immediately following the imposition of the charge. This effect is strongly significant and consistent with them following the merchants, supporting H5. However, we cannot reject that the shift of 59 percentage points for consumers is smaller than the 67 percentage point shift for merchants so not all consumers appear to be following the merchants. In addition, looking at all periods in phase 2 the proportion of consumers in downtown (14%) is significantly smaller than the proportion of merchants in downtown (22%), which is evidence against H5. These numbers also imply that consumers are choosing their preferred location more frequently than are merchants and we cannot reject H7: this behavior is consistent with signaling their preferences.

We therefore look in more detail at individual consumer choices to determine if the adjustments are due to consumers signaling a desire for the game to shift to the perimeter by not following the merchants that are staying in downtown.

Figure 5 shows the proportion of consumer choices in phase 2 of treatment 1 that are on the perimeter route even when there is no merchant there, by period. The proportions are calculated based on all periods in which no merchant is on the perimeter. To distinguish these tactics from simple choice errors we compare the proportion on the perimeter without a merchant to the proportion in downtown without a merchant. Taking the downtown route without a merchant being there must be considered an error since the loss in shopping value plus the charge would result in significantly lower earnings than in the perimeter equilibrium. There are 334 observations (across all periods in all treatment 1 sessions of phase 2) where a consumer has a chance to signal the perimeter since no merchant is on the perimeter, compared to 932 similar observations in downtown. We find that consumers choose a perimeter without a merchant 40% of the times when they have the opportunity to do so. The corresponding percentage for choosing downtown without a merchant is only 2.8%. The difference between these proportions is significant and provides evidence that consumers are signaling that they would prefer the game to move to the perimeter. As can be seen in Figure 5, the strongest signaling is found in periods 13 and 14. These signals are costly to the consumers. On average net earnings in treatment 1 when signaling is -$0.44 while they are $1.24 across all other choices.

Do we see the same type of signaling behavior in treatment 2? Figures 3b and 3d show an immediate drop in the overall proportion of consumers on the perimeter, but it is much weaker than the drop from downtown to the perimeter in treatment 1: from 100% to about 81%. However, this change is still significant. This is consistent with the pattern we saw for merchants in Figure 6 and thus indicates that consumers generally follow merchants. However, just like in treatment 1 we find that consumers choose downtown less frequently than merchants both immediately in period 11 and on average across all periods in phase 2 and we therefore again reject H5. Across all periods the proportion of merchants in downtown is 8% while it is 4% for consumers and this difference is strongly significant. We cannot reject H6, that the game converges on the perimeter, or H7, that consumers are signaling.

Looking in more detail at route choices by individual consumers in treatment 2 we can more closely investigate how consumers are deviating from merchant locations. Figure 6 shows the proportion of consumer choices in the $3 phase of treatment 2 that are on the perimeter route when there is no merchant there. Such route choices lead to earnings losses for consumers: while they avoid the $3 charge, their travel time is longer and they cannot take advantage of the superior shopping values from the merchants. As we did for treatment 1 we compare this proportion to the proportion in downtown without a merchant to test if we have an intentional pattern rather than just errors or explorations. There are 125 observations (of all periods in all sessions) with at least one perimeter that has no merchant, compared to 177 observations with no merchant in downtown. We find that consumers choose a perimeter without a merchant 46% of the times when they have the opportunity to do so. This is significantly larger than the 0.01% of times that consumers choose downtown when no merchant is there. This provides evidence that consumers are signaling that they would prefer the game to move to the perimeter also in treatment. The strongest signaling is found in periods 12 and 13. The propensity to signal in treatment 2 is not significantly different from in treatment 1. These signals are costly: net earnings when signaling are -$0.32 while they are on average $1.49 for all other choices.

Finally, we want to investigate if consumers behave as if they are anchoring on past prices such that they show a higher proportion of downtown choices in treatment 2 than in treatment 1. We find the same thing for consumers as we found for merchants: in period 11 immediately following the change in the congestion charge we see that the proportion of consumers in downtown is higher in treatment 2 than in treatment 1, consistent with price anchoring, but this is not significant. Pooling over the last 5 periods of phase 2, there is a significant difference between the treatments but it is in the opposite direction from what price anchoring would imply. We can therefore reject H8: we see no evidence of price anchoring in our data.

We also cannot reject H6, that the game converges on the efficient equilibrium, the perimeter. There is a significant difference across treatments, however. During the last 5 periods 19% of merchants are in downtown in treatment 1 but only 4% are in downtown in treatment 2. This difference is significant. Similarly for consumers, we see 12% in downtown in treatment 1 and only 2% in treatment 2. This is also a significant difference. Thus, the past experiences have an effect such that the game ends up in an equilibrium with significantly more activities in downtown when the history involved the downtown dominant strategy than when it involved the perimeter dominant strategy. This is consistent with anchoring due to priming during the first phase of the game, where downtown is the dominant strategy for consumers. Even if downtown is no longer a dominant strategy, and not even preferred by consumers, it has a lasted influence on play in phase 2 as stated in H9.

4. Related experiments

4.1 Comparative statics experiments and signaling games

Similar to our game, Sitzia and Zizzo (2012) model separate treatments where participants experience increases or decreases in prices in an individual consumer choice setting where there is uncertainty about the consequences of the choices. The choice object is a complex lottery with known probabilities and prizes. Sitzia and Zizzo (2012) find that experimental participants, who have experienced relatively high prices in the past, later display a higher demand for the lottery than do participants who have experienced relatively low prices in the past. Our experiment obviously differs from their individual consumer choice setting in that it is an interactive sequential game between merchants and consumers. The experiments are similar in that participants experience a change in prices and the initial prices may affect behavior after the change. If our consumers are anchoring on past prices, as in Sitzia and Zizzo (2012) we would expect less downtown activities when prior experiences involve relatively low congestion prices compared to when they involve relatively high prices. Payoffs are non-linear and not completely transparent, thus matching the use of uncertain monetary lotteries in Sitzia and Zizzo (2012). We do not find any evidence of price anchoring in our experiment, contrary to what they found. This may not be surprising considering that past congestion prices may not be seen as reflecting the value of shopping downtown.

Cooper and Stockman (2011) is another experiment where players are given different experiences in a phase one and then make decisions in a common game in a subsequent phase. The game is a Minimum Contribution Set (MCS) game with three players. Contributions by two of the three players is required for the public good to be provided. Treatments differ by whether the first phase of the game is played sequentially or simultaneously, and whether the contribution costs are the same or different across players. The second phase of the game is the same across treatments: sequential with different contribution costs. The simultaneous Minimum Contribution Set game has 4 pure strategy NE based on payoffs as the only utility argument, defined according to which players contribute. As long as 2 of the 3 players contribute, which is true in three of the equilibria, the equilibrium is efficient. Nobody contributing is also an equilibrium, but it is inefficient. There is a unique subgame perfect NE in the sequential version of the game where the first player does not contribute. If the third player only cares about his money payoffs he should always contribute if only one other player has contributed at that point, but concerns about reciprocity would push play away from the subgame perfect NE.

The goal of the Cooper and Stockman (2011) study is to better understand how negative reciprocity by the critical third players may change with past experiences. In particular, they want to test three hypotheses: the constructed preference hypothesis, the discovered preferences hypothesis, and the reference-point hypothesis. They find that the differences in experience in the first phase cause only a temporary difference in behavior in the second phase. By the end of the game play across the two treatments is virtually indistinguishable. This implies that the observed behavior is consistent with the second hypothesis of discovered preferences. Either way, under both the constructed and the discovered hypothesis behavior can be influenced by anchoring on past experiences which makes behavior sensitive to possible priming. Priming effects refer to cases where details of subject's previous experience which are no longer payoff relevant establish a precedent for how current decisions should be made. Priming is relevant both in their and our experiment.

Brandts and Cooper (2006) investigate the behavioral effects of changing financial incentives in a coordination game within-subject. The underlying game is a weak-link game where productivity to the firm is determined by the lowest effort levels among the employees. Employees are paid a bonus based on the profits of the firm, which are higher when employees are coordinating on high effort. While all employees benefit from coordination, when the bonus rate is low the benefits to an individual employee of signaling coordination is small compared to the risk that others do not follow. In such cases the signaling individual would incur a high cost due to the higher effort, with no immediate benefit from increased earnings through the low bonus percentage. In the game players first experience several periods of coordination failures under low bonus conditions, but when bonuses are increased coordinating on high effort is more attractive and generates coordination on high efforts. While our game in phase 2 can be seen as a coordination game between merchants and consumers, merchants have nothing to gain by relocating to the efficient equilibrium. Further, our game is sequential and not simultaneous.

Cooper and Kagel (2008) model a limit pricing game with a potential entrant facing an incumbent monopolist with either high or low cost. The entrant cannot observe the cost condition of the incumbent, but can observe output decisions before an entry decision is made. The incumbent therefore has an incentive to signal, i.e. to strategically manipulate its output, to influence the entrant's beliefs about incumbent cost. The game has multiple equilibria, including both a pooling and a separating equilibrium. Players first learn to play the pooling equilibrium and then participate in a related game where payoffs are changed to support only a separating equilibrium. They test whether the learning of playing strategically in the first game transfers to the second game. In the first game, high cost monopolists act strategically, imitating low cost monopolists. Payoffs to the entrant are then changed so as to eliminate the pooling equilibrium, leaving only the separating equilibrium. Strategic play in the second game requires very different actions than in the first game. In control sessions players played only the second game. They find that learning to play strategically in the first game can transfer to strategic play in the second game. The mechanism through which this happens is a growing portion of sophisticated learners as experience is gained, where the sophistication lies in the ability to anticipate how other agents will play. Signaling in their game is quite different from signaling in our game. In their game there are incentives to send deceptive signals, while no such incentive is present in our game.

Potters and van Winden (1996) model an asymmetric information signaling game where a first mover observes the true state of the world and can then choose to send a signal indicating the state of the world truthfully or deceptively or to send no signal. Player 2 responds to the signal by choosing one of two actions. When the state of the world is T1 there is a conflict regarding which action benefits which player, so that if player 1 signals T1 the second player is predicted to respond by choosing an action that gives the first player nothing. By deceptively sending signal T2 when T1 is the true state, assuming player 2 believes this signal, the response gives player 1 a positive payoff but nothing to player 2. When the true state is T2 the best response by player 2, to signal truthfully, gives both players a positive payoff. The experiment varies the prior attractiveness of choosing the second action and the signaling cost on a between subject basis. The purpose of the paper is to test whether play is strategic or non-strategic in the sense of players assuming others are simply random. The behavioral effects of the parametric changes they perform are more consistent with the non-strategic model. Other evidence that play is non-strategic is found in Brandts and Holt (1992, 1993) and Cooper et al. (1997a,b). Comparing this signaling environment to our game, we do have asymmetric information in that payoff feedback is private, but there is no conflict in our game and no reason for deception.

Potters, Sefton, and Vesterlund (2007) also investigate signaling in a sequential contribution game, but with two players rather than the three of Cooper and Stockman (2011). The game has asymmetric information with only the first mover knowing the returns of the public good. The contribution choices by the first mover serves as a signal in that a high contribution may be interpreted as a high return. An alternative explanation is that the first mover is making a high contribution in order to generate positive reciprocity. Such reciprocity motivated actions can lead to higher contributions in sequential than in simultaneous games. By comparing behavior in these asymmetric information games to that in full information games they are able to identify the influence from signaling and reciprocity. They do find that the information conditions influence contribution levels and conclude that behavior is more consistent with signaling than with reciprocity.

Inspired by findings reported in the psychology literature that meaningful, natural contexts assist agents in making choices based on sophisticated reasoning processes, Cooper and Kagel (2003) tests this in a sequential signaling game. The game is the same limit pricing model as in Cooper and Kagel (2008). The experiment uses treatments that differ in whether the context is generic or meaningful. In the generic context players are referred to as “A” or “B” and other terms are equally neutral. The meaningful context uses terms such as “existing firm” and “other firm” with choices between entering “this” market or some “other” market. While they do not find evidence of context changing reasoning processes in significant ways, they do find that players learn and adjust quicker. Thus, context can serve as a partial substitute for experience. Since our experiment uses a meaningful context we expect that our players learn quicker than they otherwise would. It is therefore possible that the stability we see during the final 5 periods of each phase in both treatments is a sign that play has settled in and would continue beyond the 10 periods.

4.2 Transportation experiments

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 simultaneous route choice experiment with groups of 18 where congestion is endogenously determined. The game has multiple pure strategy equilibria and 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.

Field experiments on congestion pricing confirm the general findings from the Stockholm and London studies that pricing is an effective way of decreasing congestion. However, they 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.

5. Summary and Conclusions

We design and implement an experiment with a sequential game between merchants and consumers who travel by car to investigate responses to changes in congestion charges. The debates around congestion charges have expressed concern over economic activities leaving the city centers and moving to perimeter locations and that the adjustments around these relocations can generate costs to retailers. While the most analyzed congestion charging cases of London and Stockholm show no evidence of detrimental effects on average, there are some specific cases indicating that shoppers who travel by car react by avoiding city centers during charging hours. We provide further evidence that congestion charges can cause retail activities to leave the city centers based on our experimental data, and that these adjustments are costly.

The game involves 2 merchants, who make location decisions first, and 6 or 8 consumers who subsequently make shopping and travel decisions. Payoff consequences to consumers are non-linear and non-transparent, and payoff feedback is given individually, making it difficult for players to choose strategies without experience. Under such circumstances preferences may not be known with certainty, opening up the possibility that consumers may anchor on past prices or experiences. We implement two treatments. Phase one in both treatments are dominant strategy games. In treatment 1 the dominant strategy is the downtown and in treatment 2 it is the perimeter. This phase provides different anchoring points both in terms of prices and experiences that may influence play in the second phase of the experiment. Phase 2 has multiple equilibria where one is efficient. The equilibria in phase 2 include continued play of the phase 1 equilibria which would replicate the findings in London and Stockholm.

While our main interest is in treatment 1 where congestion charges are introduced into a city with no prior charges, as a control we also include a treatment where the changes to congestion charges are reversed. This serves as a test that the behavioral forces we observe in the main treatment are general and not specific to its temporal ordering. From a policy perspective this also models the possibility that 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 price levels they have to anticipate how drivers will respond, not only to the initial price levels, but also to subsequent potential price adjustments.

We find that initial play in phase 2 reflects the price changes in a standard inverse price-demand way. Increasing the charge leads to less shopping in downtown and decreasing the charge leads to more shopping in downtown. Over time, however, play converges on the efficient equilibrium in both treatments. During the adjustment consumers engage in costly signaling by selecting the perimeter even when it is not in their immediate best interest to do so. The past experiences from phase one also have an effect on equilibrium selection. The game ends up in an equilibrium with significantly more activities in downtown when the history involved the downtown dominant strategy than when it involved the perimeter dominant strategy. This is consistent with players anchoring on past experiences due to priming effects (Tversky and Kahneman (1974), Cooper and Stockman (2011), and Ariely, Loewenstein, and Prelec (2003)).

What are the implications for traffic planning from these findings? The good news first: if congestion charges are very low or very high such that they lead to dominant strategies play converges quickly. Further, if the congestion charge implies multiple equilibria and therefore a selection problem there is a good chance that traffic eventually converges on the efficient equilibrium even when payoff consequences are not fully transparent. In both of our treatments we see that the efficient equilibrium, the perimeter, attracted a large share of players, with the exception of a small share who may have been affected by priming. However, the bad news is that there is also a real risk for costly misallocations of merchant activities immediately following a change in the charge. In treatment 1 merchants who stay in downtown experience reduced sales when consumers decide to shop on the perimeter. In treatment 2 there is an initial move away from the perimeter that eventually reverses, also implying lost sales and transition costs to merchants. In the field such dynamics can be very costly due to the time and resources that are required for reallocating commercial investments.

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Figure 1: The Network

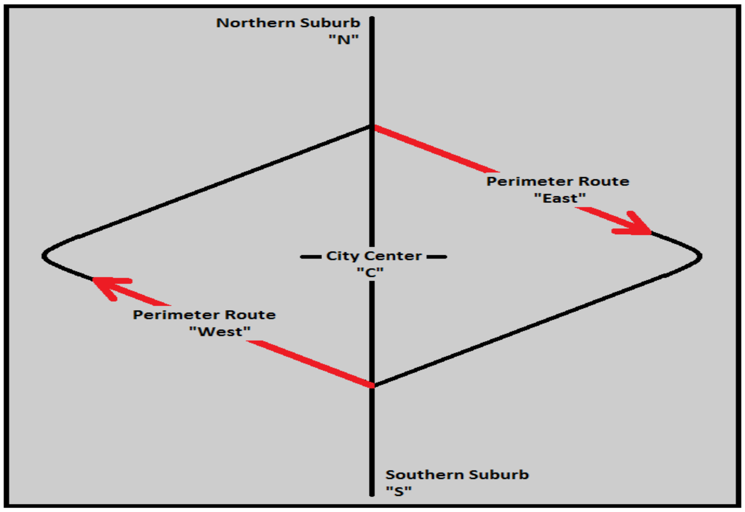


Table 1: Travel Time Costs

	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: Consumer Payoffs and Best Responses: Afternoon

	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 consumer. The earnings for a south consumer are qualitatively similarly, but differ slightly due to different travel time costs.
*** Equilibrium Predictions

Table 3: Equilibrium Prediction Summary: Afternoon

Merchant location choices	$0 toll		$3 toll		$4 toll	
	AM	PM	AM	PM	AM	PM
	Cosumer 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 drives and the column PM shows predictions for afternoon drives. The text in each cell shows the predicted choices for the consumers. Merchant locations do not matter to AM consumer choices.
*** Equilibrium predictions in afternoons.

Table 4: Consumer 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: Consumers' Choices in the Morning by Period

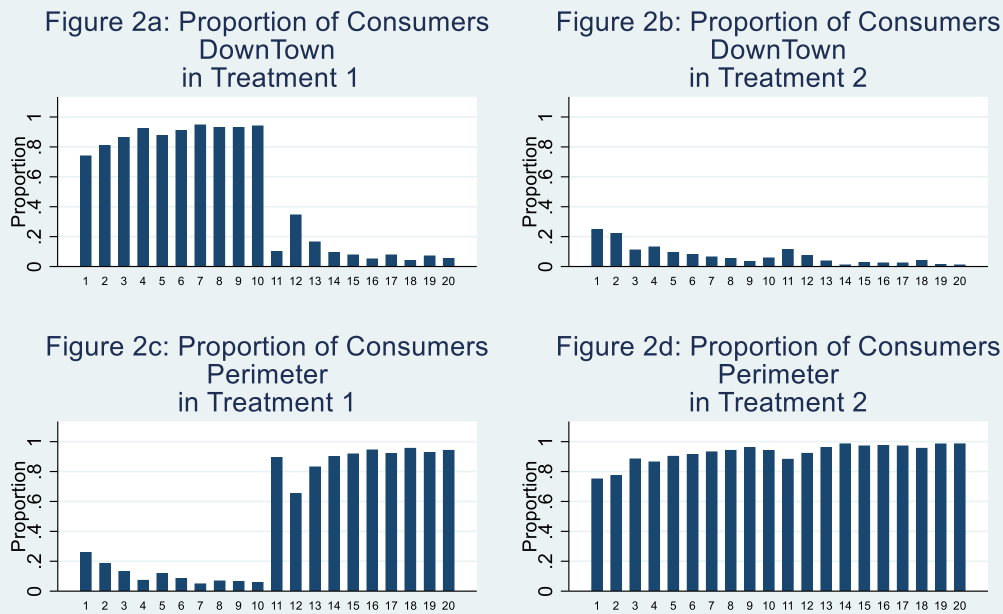
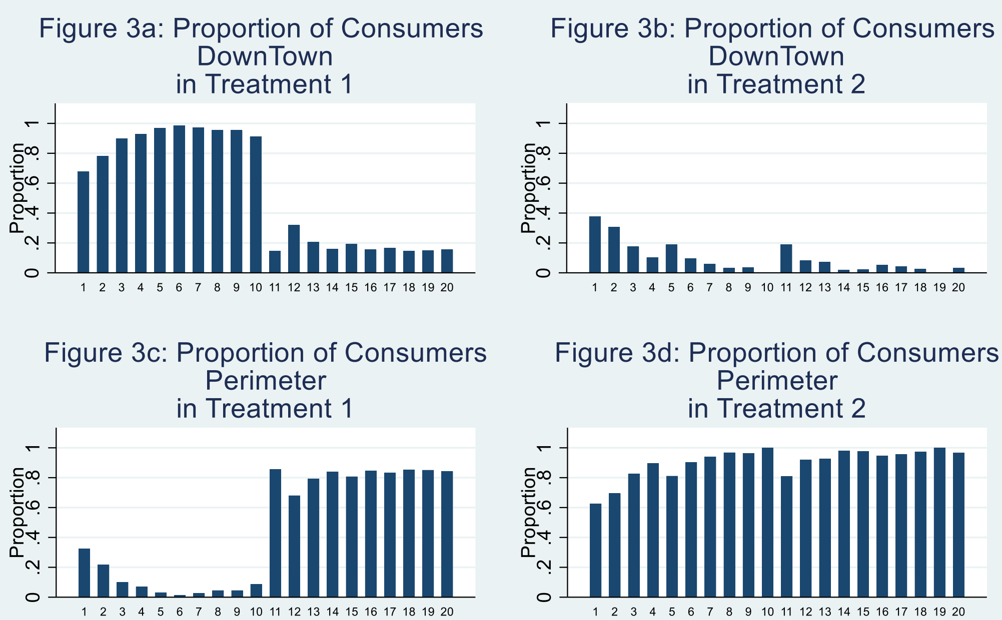


Figure 3: Consumers' Choices in the Afternoon by Period



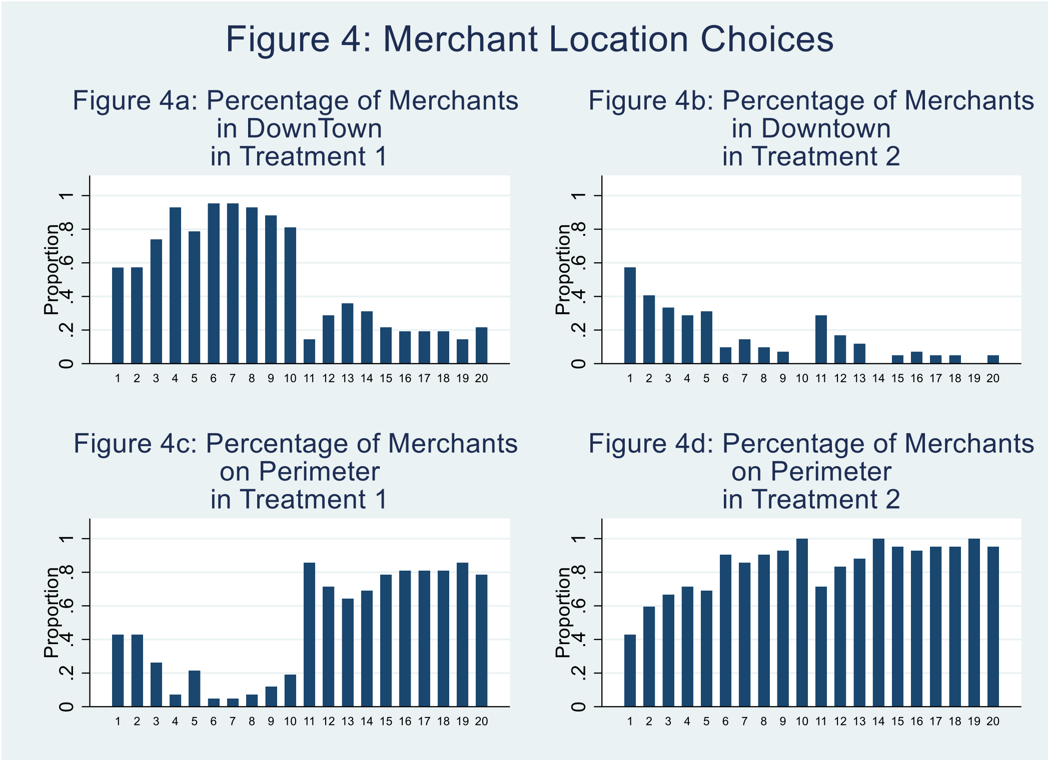


Table 5: Proportions of Merchants in Each Location Compared to Random Location Choices

	\$0 charge	\$3 Treatment 1	\$3 Treatment 2	\$4 charge
Both in downtown	68% (p<.001)	10% (p<.001)	1% (p<.001)	9% (p<.001)
Both on perimeter	5% (p<.001)	65% (p<.001)	84% (p<.001)	62% (p<.001)

N=210, p-values from proportions tests for the hypothesis that proportion=.25.

Table 6: Average Number of Merchants in Downtown and on Perimeter

	\$0 charge	\$3 treatment 1	\$3 treatment 2	\$4 charge
Downtown	1.62 (p<.001)	.45 (p<.001)	.17 (p<.001)	.46 (p<.001)
Perimeter	.38 (p<.001)	1.55 (p<.001)	1.83 (p<.001)	1.54 (p<.001)

N=210. P-values for t-tests that average number of merchants equal the expected number 1.

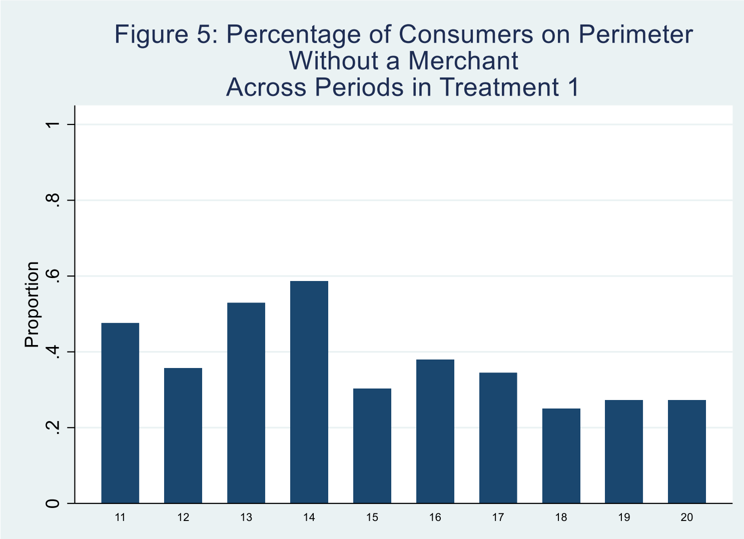


Figure 5: Percentage of Consumers on Perimeter Without a Merchant Across Periods in Treatment 1

Note: The figure shows consumers who locate on the perimeter when there is no merchant as a percentage of all the times that one or both perimeters have no merchant. Thus, it shows the propensity to signal perimeter choices when such signals are possible.

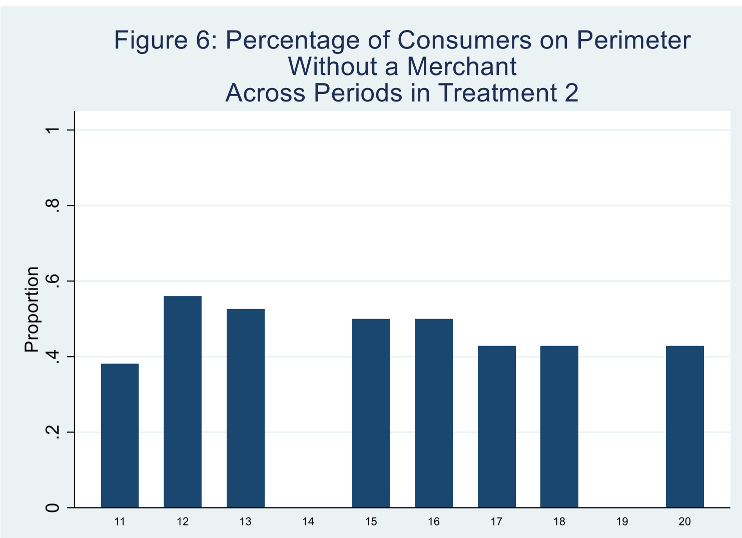


Figure 6: Percentage of Consumers on Perimeter Without a Merchant Across Periods in Treatment 2

Note: The figure shows consumers who locate on the perimeter when there is no merchant as a percentage of all the times that one or both perimeters have no merchant. Thus, it shows the propensity to signal perimeter choices when such signals are possible.