

# The role of consumer loyalty and preference for variety in Chicago gourmet food truck location choice

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## Introduction

The popularity of gourmet food trucks has surged to the point where graduates of elite business schools are competing with top chefs to attract a following of customers in major US cities. Every day these food truck owners decide where to park for breakfast, lunch and dinner service and whether to do each service. Most food trucks only choose to serve lunch from a street location (they do not serve breakfast and serve dinner at private events or public festivals). In choosing a parking location from which to serve lunch, food trucks face a location choice problem distinguished by trivial re-location costs, consumer loyalty dynamics, and demand-side agglomeration effects. Food truck movement between locations over time thus provides a novel opportunity for examining the relative importance of consumer loyalty and preference for variety to lunch choice

I propose a simple model for consumer lunch choice that gives a role to both loyalty and preference for variety as demand drivers. I then proceed to estimate the parameters of a possible food truck profit function to determine whether food trucks are rewarded for moving in response to consumer loyalty dynamics or preference for variety. Identification is achieved through assuming Markov Perfect equilibrium play and applying the two-step estimation procedure outlined in Bajari et al. (2007). Whether consumers are more motivated by loyalty or a preference for variety in lunch choice is an important question for the restaurant industry and findings here will likely generalize to other choice situations.

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\*Thanks Chad Syverson for advising

# Literature Review

Work examining firm location choice dates back to Hotelling (1929). Hotelling's boardwalk model considered two identical firms locating along one dimension and concluded that the two firms should both locate in the center in equilibrium. Hotelling's model explains why within a given region of a city food trucks are observed to park right next to each other rather than spread out along a block or across several blocks. But Hotelling's model does not explain why food trucks are observed to move between locations over time. That food trucks are observed to move between locations over time necessitates enriching Hotelling's model and provides a novel opportunity to examine the relative importance of different features of consumer choice behavior—food trucks may move between locations in response to consumer preference for variety or consumer loyalty.

The literature has found a consumer preference for variety with several components. Consumers may generally prefer to choose from larger menus up to some point because they gain satisfaction from imagining themselves using products available, but unchosen. See Oppewal and Koelemeijer (2005) and Kaiser and Schwabe (2009) for further discussion. Consumers also tend to prefer to comparison shop in industries where there is an incentive to personally inspect the good before purchasing. Marshall (1920) provides an early version of this mechanism leads to increased consumer demand at shopping locations where several retailers are simultaneously selling a variageted produce. Having a variegated product in a single location lowers consumer search costs, which increases the likelihood of visitation, and thereby heightens the demand experienced by agglomerating firms. Fischer and Joseph E Harrington (1996) build on this logic with a theoretical model showing that the benefit of agglomeration increases with the heterogeneity of the product. Finally, literature on brand switching suggests that consumers can become satiated with repeatedly purchasing a certain brand and so change to another brand. These three mechanisms together constitute a consumer preference for variety that food trucks likely more in response to. To the extent that consumers are repeat visitors of the food truck parking location, truck movement increases the variety available beyond mere collocation of several trucks.

Consumer loyalty in restaurant selection and the role of habit in food choice is also well documented. Consumers return to restaurants that have provided high service quality in the past and

do not return to restaurants that have provided low service quality. See Barber et al. (2011) for a discussion of service quality components studied. In particular, Jin and Leslie (2009) show the importance of a reputation for hygiene for chain restaurants in Los Angeles. Further, consumers develop brand loyalty to specific restaurants. *Still looking for good citations here, but likely few customers actively switch between McDonalds, Burger King, and Wendy's and many customers are loyal to a favorite neighborhood restaurant.* Beyond choice of restaurant, Honkanen et al. (2005) find that habit plays an important role in consumers choice to eat seafood. Food truck movements (or lack thereof) between locations might then be in response to consumer loyalty. Food trucks could be encouraged to park repeatedly in a single location to the extent that consumers gain habit or loyalty stocks. Alternatively, if consumers gain habit stock faster than they lose it, food trucks may be incentivized to circulate through locations.

## Model

I first propose a model of consumer demand for lunch that incorporates a preference for variety and consumer loyalty dynamics. I then consider how food trucks maximize a period profit function and reach a Markov Perfect equilibrium.

### Consumer choice over lunch options

Assume a consumer maximizes her utility from the lunch option chosen minus the search cost. The consumer faces a search cost  $c(L)$  increasing in the number of lunch options,  $L$ , considered in the choice set. These  $L$  lunch choices are indexed by  $l$  with “food trucks” being the choice to walk to the closest street intersection where food trucks park. “Food trucks” is a distinguished choice (as might be a cafeteria that has a number of different restaurants inside) because the consumer benefits by gaining access to a large number of lunch options with limited additional search cost.

Consumers could be strongly influenced by habit in making a lunch choice, so take the latent utility from a lunch option on a given day  $t$  as  $u_{lt} = s_{lt} + \epsilon_{lt}$ . Here  $s_{lt}$  is the habit stock that evolves over time, building when the lunch option chosen is  $l$  and depreciating otherwise, so that

$s_{lt} = (1 - \delta_l)s_{l,t-1} + \lambda_l I\{choice = l\}$ . Meanwhile,  $\epsilon_t$  is a normally distributed vector of taste shocks with mean  $\mu_t$  and variance  $\Sigma_t$ . Together  $\mu_t$  and  $\Sigma_t$  can account for the possibility that consumers become satiated with a lunch option and want to switch over time.

Again, “Food trucks” is a distinguished choice. Index the food trucks operating in the city by  $i$ . The stock  $s_{lt}$  for “food trucks” is a sum over sub-stocks  $s_{lit}$  ( $s_{lt} = \sum_{i=1}^N s_{lit}$ ). The summation here provides a further variety reward that captures that consumers may prefer choosing from a larger menu. Similar to the general case,  $s_{lit}$  evolves as  $s_{lit} = (1 - \delta_{li})s_{li,t-1} + \lambda_{li} I\{choice = l_i\} - \gamma_{li} I\{choice = l\} I\{l_i \text{ unavailable}\}$  and is reset to 0 should it go negative. Here  $\gamma_{li}$  incorporates the disappointment consumers receive if they choose “food trucks” and a given truck is not there. Having chosen to walk to food truck parking location, consumers order from the food truck that they have the highest stock in or order randomly if they do not have a stock in any food trucks present. Alternatively, it is possible to incorporate an additional set of taste shocks here to create more realistic choice over the food trucks available.

That consumers prefer variety and build loyalty stocks creates a non-trivial dynamic location choice problem for food truck  $i$ :

- Visiting a new parking locations (or cycling through locations) increases demand for the food truck through heightening consumer demand for food trucks generally by increasing the variety of food trucks each consumer encounters
- Repeatedly visiting a parking location increases the habit stock of consumers and so leads to higher expected demand at that location (a larger pool of consumers is more likely to visit the truck for lower taste shocks)
- Visiting a new parking location (or cycling through locations) increases demand for the food truck to the extent that consumers build habit stock in a truck faster than they lose it for some range of stock

## Food truck location choice

Motivated by the above, consider the  $N$  food trucks (again indexed by  $i$ ) operating in the city. Each day these trucks take the action  $a_{it}$  to serve lunch in one of  $J$  locations or not to operate (so there are  $J + 1$  possible actions available to each truck). With slightly different emphasis, it may perhaps be helpful to think of the food trucks as playing an entry/exit game with entrance into  $J$  markets being considered. The food trucks employ a Markov Perfect strategy in choosing each day's parking location based on the current state vector and their current private information shocks.

To motivate the state space, consider a food truck owner sitting down with his staff on Sunday afternoon to review the outcomes from the proceeding week and to plan the schedule for the upcoming week. With this in mind, I take the state variable  $s_t$  to contain the day of the week, quarter of the year, an indicator for holidays (*to be added*), and summary statistics of truck movements over the last calendar week:

- Number of trucks by action
- Diversity of trucks by action
- Frequency with which each truck has chosen each action

The food truck owner chooses a parking location based on this state and her private information so as to maximize expected discounted profit. Note that the summary statistics of truck movements over the last calendar week only update weekly, but each day the food truck owner receives a new private information shock, observes the day of week, quarter, and holiday status and makes a parking location choice incorporating this new information.

The food trucks profit from a lunch service is a markup times the quantity sold. The quantity sold is a random variable parameterized linearly in the state variables, functions of the current actions of the other trucks and a T1EV error term  $n_{it}$  (which is a vector of error terms, one drawn for each possible action):

$$\pi_{it}(a_t, s_t, n_{it}) = (p - c) * Q(a_t, s_t, n_{it}) = \beta_0 + f(s_t, a_{it}) * \beta_1 + g(a_t) * \beta_2 + n_{it}(a_{it})$$

Here  $f(s_t, a_{it})$  is a vector that contains the state variables that correspond to the parking location chosen by truck  $i$  for lunch service at time  $t$ . That is,  $f(s_t, a_{it})$  contains the number and diversity of trucks at the parking location chosen along with the frequency with which truck  $i$  has chosen this parking location over the last calendar week. The vector also contains fixed effects for day of the week, quarter of the year and whether the current day is a holiday. Similarly,  $g(a_t)$  is a vector composed of a dummy indicating the parking location chosen along with the number and diversity of trucks who chose the same parking location concurrently. Profit is set to 0 if the truck decides not to park for the lunch service.

Of interest is how the number and diversity of trucks concurrently parking at a location impacts truck profit relative to how the historic frequency of parking at a location impacts truck profit. This comparison speaks to the relative profit implications of consumers' preference for variety and consumers' loyalty to a specific food truck. Both consumers' preference for variety and the evolution of consumers' loyalty or habit stock could encourage (or discourage) food trucks from moving between locations. Collocation could increase profit through heightening consumer demand, but the increased competition simultaneously exerts downward profit pressure. Movement to increase consumer demand through exploiting the dynamics of consumer habit stocks benefits the truck that can successfully keep and maintain a customer base, but the magnitude maybe small as other trucks likely move in offsetting ways. It is an empirical question as to how food trucks maximize profit by catering to these forces. I expect food trucks to be highly rewarded for increasing variety and only marginally rewarded for building and maintaining a customer base.

## Estimation

I follow the two-step procedure outlined in BBL for estimating dynamic discrete choice games under the assumption that behavior is consistent with Markov perfect equilibrium.

## Stage one

Let  $V_i(\sigma, s)$  be the food truck's ex ante value function, the present discounted value of its daily profits starting from state  $s$  when the food trucks are playing the joint Markov Perfect strategy profile  $\sigma$ . Define the choice specific value function as

$$v_i(a_{it}, s_t) = E_{n_{-i,t}}[\beta_0 + f(s_t, a_{it}) * \beta_1 + g(a_{it}, \sigma_{-i}(s_t, n_{-i,t})) * \beta_2 + \delta \int V_i(\sigma, s_{t+1}) dP(s_{t+1}|a_{it}, \sigma_{-i}, s_t)]$$

The optimal strategy for a food truck is to choose the action  $a_{it}$  s.t.

$$v_{it}(a_{it}, s_t) + n_{it}(a_{it}) \geq v_{it}(a'_{it}, s_t) + n_{it}(a'_{it}) \quad \forall a'_{it}$$

Having assumed T1EV shocks, the Hotz-Miller inversion gives that the differences in the choice specific value functions are identified as the differences in the log of the probability with which the food truck chooses each action conditional on the state

$$v_{it}(a'_{it}, s_t) - v_{it}(a_{it}, s_t) = \ln(P(a'_{it}|s_t)) - \ln(P(a_{it}|s_t))$$

As the food truck's ex ante value function is  $V_i(\sigma, s_0; \theta) = E[\sum_{t=0}^{\infty} \delta^t \pi_{it}(\sigma(s_t, n_t), s_t, n_{it}; \theta) | s_0]$  it is straight-forward to estimate through simulating a path of play:

1. Take an initial state and draw shocks  $n_{i0}$  from T1EV for each action for each truck
2. Calculate the optimal action for each truck and the resulting profits  $\pi_{it}(a_0, s_0, n_{i0}; \theta) = \beta_0 + f(s_t, a_{it}) * \beta_1 + g(a_t) * \beta_2 + n_{it}(a_{it})$
3. Update to the new state given the optimal actions and initial state
4. Repeat for T time periods and report the PDV of the profit function conditioned on the parameters

Note that the optimal action is any action that satisfies  $n_{it}(a_{it}) + \ln(P(a_{it}|s_t)) \geq n_{it}(a'_{it}) + \ln(P(a'_{it}|s_t)) \quad \forall a'_{it}$ . The parameters to be estimated in the second stage are  $\beta_0, \beta_1, \beta_2$  from the period profit function.

## Stage Two

The parameters from the period profit function are identified as the values that justify the observed Markov Perfect strategy profile over other possible strategy profiles. I consider always parking in a specific location and parking randomly as the possible alternative strategies. To use these alternative strategies  $\sigma_i^a$ , create

$$g(E_{ia}, \theta) = V_i(\sigma_i, \sigma_{-i}, s_0; \theta) - V_i(\sigma_i^a, \sigma_{-i}, s_0; \theta)$$

The parameter estimates are found as the minimum distance estimators solving

$$\min_{\theta} \int (\min\{g(E_{ia}, \theta), 0\})^2 dH(E_{ia})$$

Here  $H(E_{ia})$  is a uniform distribution over the tuples of trucks, starting state, and alternative policies considered.

## Data

Food trucks advertise their parking locations primarily through Twitter. These tweets are collected and redistributed to consumers through Twitter, cellphone applications, and web calendars. Notably, only a handful of trucks publish a schedule of future locations and all such schedules display just the current week. Chicago Food Truck Finder is one of several websites to maintain a map and calendar of truck parkings at popular spots in and around Chicago (see <http://www.chicagofoodtruckfinder.com/weekly-schedule>). The calendar is updated with the day's parking location data in real time from the tweets and contains parking records dating back to 2011.

To build the history of truck parkings, I scrape the parking records from the html files maintained by Chicago Food Truck Finder from 8/10/2011 to 8/12/2015. Over this period, there are 34,328 parkings of 171 food trucks at 29 different locations. I process this data to restrict attention to the observations informative about the parking equilibrium for lunch service in Chicago. I drop



all observations from before 2014 since a number of city laws governing food trucks changed in 2013 leading to a corresponding change in the number and type of food trucks on the road. I exclude food trucks that only serve dessert and breakfast (9 trucks) or operate for less than three months, and drop parkings outside of the city (namely in Schaumburg and Oak Brook). Finally, I only keep parkings where the food truck is scheduled to start serving food before noon and end after noon. Together these changes leave 6,227 parkings of 37 trucks at 23 locations with the restriction to data post 2013 causing most of the lost observations.

It is possible that trucks park outside of these 23 locations since Chicago Food Truck Finder only displays information for parkings at popular locations. However, even many of these 23 popular locations are rarely used. Only 8 of the 23 locations see over 150 parkings. As such, it is reasonable to simplify a food truck’s decision to parking at one of these 8 locations or choosing not to park. Dropping locations where there are fewer than 150 parkings over the two year observational period gives a final dataset with 5,598 parkings of 37 food trucks at 8 locations.

Location	Parkings
Madison and Wacker	161
Lasalle and Adams	164
450 N. Cityfront Plaza	174
Randolph and Columbus	174
Wacker and Adams	849
600 West Chicago Avenue	901
Clark and Monroe	1162
University of Chicago	2013

It is insightful to examine parking behavior of a selection of trucks. Inspection indicates that food trucks employ a variety of strategies. Below are the lunch parking locations over 3 weeks from 3 trucks (chosen to illustrate the common behaviors). Jack’s Fork in the Road alternates between just two spots. La Boulangerie parks in the same location every day. The Fat Shallot parks at a wide mix of locations potentially following a weekly schedule. Of note, as many as 15 (out of the 37 trucks seen) primarily frequent 2 or fewer locations, which is potentially indicative that building and maintaining a stock of food truck customers is an important profit consideration. The diversity of strategies employed would then suggest that trucks build and lose stocks at heterogeneous rates as might be expected.

Date	Jack’s Fork in the Road	La Boulangerie	The Fat Shallot
Thu, Jul 16	Wacker and Adams	University of Chicago	Clark and Monroe
Fri, Jul 17	NaN	University of Chicago	600 West Chicago Avenue
Mon, Jul 20	Wacker and Adams	University of Chicago	Clark and Monroe
Tue, Jul 21	Clark and Monroe	University of Chicago	University of Chicago
Wed, Jul 22	Wacker and Adams	University of Chicago	450 N. Cityfront Plaza
Thu, Jul 23	Clark and Monroe	NaN	Wacker and Adams
Fri, Jul 24	NaN	NaN	600 West Chicago Avenue
Mon, Jul 27	Clark and Monroe	University of Chicago	NaN
Tue, Jul 28	NaN	University of Chicago	University of Chicago
Thu, Jul 30	Wacker and Adams	University of Chicago	Wacker and Adams
Fri, Jul 31	Clark and Monroe	NaN	NaN
Mon, Aug 03	Wacker and Adams	University of Chicago	NaN
Tue, Aug 04	Clark and Monroe	NaN	University of Chicago
Wed, Aug 05	NaN	University of Chicago	Clark and Monroe
Thu, Aug 06	NaN	NaN	Wacker and Adams

## Results

*The Python code used to estimate the model along with the full dataset are currently available at <https://github.com/eliotabrams/BBL>. The Python code is on the way to being quite good according to a computer science BA friend, and so I may submit it after some generalization to Thomas Sargent’s repository at <http://quantecon.org/>*

*I am still working to estimate SEs for the model. It is computationally quite intense, so I am*

*waiting to meet with Gunter rather than using Ali's purchased processing time on the Midway immediately. The current point estimates for the benefit of agglomeration and repeated parking are negative (opposite of what I'd expect). I likely need to futz with the variable definition and run some sensitivity tests. I'll start on these before talking to Gunter.*

To estimate the model, I discretize the state variables for number of trucks by parking location over the last calendar week, diversity of trucks by parking location over the last calendar week, and frequency with which each truck has chosen each parking location over the last calendar week. I take each of the respective variables to be “high” if the value is above the 80th percentile observed across all weeks in the data and “low” otherwise. The 80th percentiles are 18 parkings at a given location over the week, 7 different types of trucks parking at a given location over the week, and a truck parking at a location twice over a given week.

The resulting state space has the previous week's counts at 8 locations, the previous week's diversity at 8 location, the previous week's parking frequencies of the 37 trucks at each of the 8 locations, the quarter of the year, and the day of the week for a total of 314 state variables. In order to permit identification, I assume (as is common in the literature) that each food truck makes its parking location choice based on a subset of the state variables. So again envision the owner of the food truck sitting down with her staff on Sunday afternoon to review the proceeding week and plan the next. I assume the owner makes her decisions for each day in the upcoming week based on what day it will be, what quarter of the year it will be, whether the day will be a holiday, the counts and diversity of trucks at each location last calendar week, and its *own* parking frequencies last calendar week. I take these variables to compose the decision sub-state. Across trucks, each of these sub-states appears twice in the parking records on average.

Using this refined state space, I perform the BBL procedure to estimate the parameters of the value function assuming Markov Perfect equilibrium play. These parameters are an intercept, fixed effects for each location choice, day of week, quarter of year, controls for whether the location had high truck counts and diversity the previous week, and the variables of interest—namely the coefficient on whether there are many trucks currently parked at the same location, the coefficient on whether there is a high diversity of trucks currently parked at the same location, and the

coefficient on whether the truck has parked frequently at the location in the last week.

I randomly draw 140 tuples from the space of alternative strategies and starting states considered (the intersection of acting randomly or always choosing the same location with all states realized in the data) according to a uniform distribution. I estimate each of the value functions in the corresponding  $g(E_{ia}, \theta)$  terms as the average present discounted value across 20 paths of simulated play. The paths are 130 days long (26 weeks) and use a discount rate of 0.99 to discount profit between days. The point estimates for the parameters are identified as the minimum distance estimates solving the objective created by summing the 140  $g(E_{ia}, \theta)$  terms. I use the Nelder-Mead method to perform the minimization. Standard errors for the point estimates are created by bootstrapping over the observed location choices conditional on the state and re-running the estimation procedure. I find

	Estimate	Proposed Sign
High Current Count	-19.02	-
High Current Diversity	-7.52	-
High Historic Frequency	-4.57	-
High Historic Count	7.64	+
High Historic Diversity	4.78	+
Intercept	-2.70	0
Monday	17.12	+
Tuesday	0.18	0
Wednesday	-2.64	0
Thursday	-7.26	-
Friday	4.44	+
Q1	10.73	+
Q2	5.36	+
Q3	5.55	+
Q4	4.00	+
Lasalle and Adams	-6.40	-
Randolph and Columbus	3.98	0
University of Chicago	-3.37	0
Wacker and Adams	-2.00	0
West Chicago Avenue	1.30	0
Cityfront Plaza	2.88	0
Clark and Monroe	3.33	0
Madison and Wacker	-0.93	0

*As described above, I am still working on calculating the SEs and need to futz with the variable definitions. For now, it seems that being surrounded by many other food trucks has a negative*

*profit impact (expected), that being surrounded by diverse other trucks has a negative profit impact (unexpected), that having parked more than 2 times in the previous week in the current location has a negative profit impact (unexpected), that Monday is the best day to operate a food truck, that all seasons and all locations provide roughly the same profit impact (I think this is an expected equilibrium result).*

## Conclusion

TO BE COMPLETED

## References

- Bajari, P., C. L. Benkard, and J. Levin (2007). Estimating dynamic models of imperfect competition. *Econometrica* 75(5), 1331–1370.
- Barber, N., R. J. Goodman, and B. K. Goh (2011). Restaurant consumers repeat patronage: A service quality concern. *International Journal of Hospitality Management* 30(2), 329–336.
- Fischer, J. H. and s. J. s. Joseph E Harrington (1996). Product Variety and Firm Agglomeration. *The RAND Journal of Economics* 27(2), 281–309.
- Honkanen, P., S. O. Olsen, and B. Verplanken (2005). Intention to consume seafood—the importance of habit. *Appetite* 45(2), 161–168.
- Hotelling, H. (1929). Stability in Competition. *The Economic Journal* 39(153), 41–57.
- Hotz, V. J., R. A. Miller, S. Sanders, and J. Smith (1994). A Simulation Estimator for Dynamic Models of Discrete Choice. *The Review of Economic Studies* 61(2), 265–289.
- Jin, G. Z. and P. Leslie (2009). Reputational Incentives for Restaurant Hygiene. *American Economic Journal: Microeconomics* 1(1), 237–267.
- Kaiser, K. and R. Schwabe (2009). Preference for Variety: A Representation Theorem and Implications for Industrial Organization. *manuscript*.

Marshall, A. (1920). *Principles of Economics (eight ed.)*. Macmillan (1920 [1890]).

Oppewal, H. and K. Koelemeijer (2005). More choice is better: Effects of assortment size and composition on assortment evaluation. *International Journal of Research in Marketing*.

# Appendix














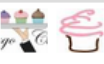
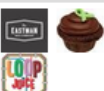
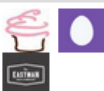

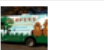


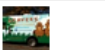
**Table 1: Truck parkings used in the analysis**

Truck	Type	Parkings
5411 Empanadas	Other	210
Blue Street Market	American	68
Bob Cha Food Truck	Asian	209
Bridgeport Pasty	Other	107
Caponies Express	Italian	258
Cheesies Truck	Italian	88
Chicago Lunch Box	Asian	242
Chicago Pizza Boss	Italian	30
Da Lobsta	American	73
Gino’s Steak Truck	Italian	197
Harold’s Chicken Shack	Meat	50
Haute Sausage	American	140
Haute and Ready	American	175
Husky Hog BBQ	Meat	131
Jack’s Fork in the Road	American	191
Jerk	Other	146
La Boulangerie	French	222
La Cocinita	Mexican	108
Mina’s	Mexican	162
Model Chef	American	52
PIKO Street Kitchen	Asian	76
PORKCHOP	Meat	73
Paris Ouh La La	French	76
Pierogi Street	Other	252
Soups in the Loop	American	289
Southern Pitch	American	38
Tamale Spaceship	Mexican	254
Taquero Fusion	Mexican	173
The Corner Farmacy	American	80
The Fat Shallot	French	261
The Jibarito Stop	Mexican	135
The Roost Truck	Meat	314
The Salsa Truck	Mexican	99
The Slide Ride	American	208
Windy City Patty Wagon	American	182
Wow Bao	Asian	105
Yum Dum Truck	Asian	124

Table 2: Portion of Chicago Food Truck Finder Weekly Schedule

The Week of Aug 8, 2015

This schedule represents the current week's truck schedule for **popular** food truck spots.

	<div> <div>←</div> <div>Today</div> <div>→</div> </div>						
	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Clark and Monroe, Chicago, IL							
Lasalle and Adams, Chicago, IL							
Wabash and Jackson, Chicago, IL							
Willis Tower							
Madison and Wacker, Chicago, IL							
Wacker and Adams, Chicago, IL		