What's Behind the Food Truck Phenomenon? Information Frictions and Taste-for-Variety*

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Abstract

We study the economic causes and consequences of the recent explosion in gourmet food trucks. We argue that 1) new mobile communication technology enabled food truck growth by relaxing an information friction complicating their business model and 2) that an important advantage of food trucks over brick-and-mortar restaurants is that trucks can use mobility to capitalize on consumers' taste-for-variety. We use novel data from the internet, including food trucks' real-time Twitter feeds, to support our theory. We also provide evidence suggesting that the growth in food trucks has increased social surplus for urban consumers by increasing access to food variety.

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1 Introduction

Gourmet food trucks are a rapidly growing phenomenon in major U.S. cities. Figure 1 shows that food truck revenues started growing very rapidly in 2007, achieving 50% growth in revenue over 5 years and reaching $1.5 billion in 2012.[1] The growing food truck phenomenon has attracted much attention from popular media and has raised a host of issues for local policymakers related to congestion, taxation, and opposition from those who are negatively affected by food trucks. In this paper, we ask: What underlying economic forces are driving the rapid growth in gourmet food trucks?

We formalize and then provide empirical evidence for two underlying factors driving the growth in food trucks. First, we argue that the introduction and proliferation of new mobile communication technologies (e.g. smartphones and social media) have relaxed an information friction complicating the entire food truck business model. To be more specific, we argue that technology allows food trucks to broadcast their location information to consumers in real-time, which reduces consumer uncertainty and increases demand for and profitability of food trucks. Indeed, Figure 1 shows that food trucks began growing rapidly in the same year that the iPhone—one of the first popular smartphones capable of accessing the internet from anywhere—was first released.

Second, we argue that one of the main advantages that food trucks have over brick-and-mortar restaurants is that they can serve different consumers each day by switching locations. By reducing information frictions associated with changing locations, mobile technology allows food trucks to better capitalize on consumers' taste-for-variety. One consequence of the food truck industry's growth is therefore that consumers have access to a greater variety of restaurants in close proximity than they would have had otherwise.

We begin the paper by developing a theory that illustrates our two mechanisms. Consider a consumer who is deciding whether or not to eat at a nearby

[1]Although we do not have revenue data for other countries, Google searches for "food trucks" have increased rapidly in other countries, suggesting that food trucks may be a growing phenomenon in other countries too.

food truck when there is no mobile technology. In order to purchase from the food truck, the consumer must pay a cost to visit the truck's expected location, but there is some probability that the truck will not be there (if, for example, the truck was unable to find a parking space). This *locational uncertainty* reduces the expected value the consumer receives from visiting the food truck, and therefore reduces the size of the market for the truck at any given location. The reduction in market size may be large enough that a restaurant owner would prefer to operate as a brick-and-mortar store (which does not suffer from locational uncertainty) instead of a food truck, or to not operate at all. Consider now an alternative scenario in which the food truck can broadcast its location in real-time to the consumer using new technology. Consumers equipped with a device for receiving the broadcast no longer face uncertainty about the food truck's location. The size of the market is therefore not reduced and so technology increases the market for food trucks.

We model consumers as having a *taste-for-variety*, so that all else equal, they would prefer not to eat at the same restaurant in consecutive days. With this preference structure, the introduction of mobile technology can make it more profitable to operate as a food truck than a brick-and-mortar, even if the costs of operating are the same. This is because, with technology, mobility becomes an advantage for food trucks: they can visit different locations day-by-day to capitalize on consumer taste-for-variety, and they can mitigate the associated information costs by broadcasting their location to consumers in real-time. Consumers are also better off due to their increased access to food variety.

To provide empirical support for our theory, we first confirm the broad prediction of the model that there is a link between smartphones, social media and food truck growth. Using MSA-level Google search data from Google Trends, we show that growing search interest in smartphones and social media corresponds to growing search interest in food trucks. Moreover, the relationship passes a test for Granger causality; we find that past search interest for smartphones and social media predicts search interest for food trucks while future interest for smartphones and social media does not. The results are robust to alternative explanations such as changing food attitudes or demographics.

While the Google search analysis suggests a causal link between mobile technology and food trucks, it does not directly test whether the particular mechanisms in our model are responsible for the connection. To add stronger evidence for our specific theory, we use rich micro-evidence from Washington D.C. food trucks to show that 1) locational uncertainty generates an information friction that is alleviated by mobile technology and 2) food trucks choose different locations day-by-day in order to take advantage of consumers' taste-for-variety.

To test for locational uncertainty, we downloaded the Twitter feeds for all individual food trucks operating in Washington D.C. from 2010 to 2013. We find that most trucks use twitter at a daily frequency to announce their location choices and that many of these location related tweets are used to indicate a change of location due to unforeseen circumstances such as parking and traffic difficulties. Our results imply that in 1 out of every 13 days, the typical truck will not be at its expected location at the expected time, suggesting that locational uncertainty is a significant friction. Furthermore, the timing of the tweets (which we observe down to the second in our data) suggests that circumstances often require a change of plans at the last minute (e.g. right before the lunch hour) and thus the ability to send real-time updates using smartphones and social media is indeed important. Overall, the Twitter data strongly suggests that locational uncertainty is a significant obstacle to the food truck business model, but that food trucks use mobile technology to mitigate its effects.

To test for the presence of taste-for-variety, we collect a panel dataset on D.C. food truck location decisions. For each food truck, we observe its *daily* lunch-time location decisions from the beginning of May 2012 to the end of March 2013. Estimating a discrete choice model of food truck location decisions, we find that food trucks are very unlikely to locate in places that they have visited recently. The effect is strongest for locations that were visited just one day ago, becomes weaker as the length of time between visits increases, and dies out after about one week. The magnitude of the effect is economically significant: the implied loss in profits from visiting the same place two days in a row is on the same order of magnitude as the effect of a rainy or snowy day, or of the imposition of a 10% sales tax. Considering that the primary market for our food trucks are office workers who are fixed to their locations by exogenous reasons, the tendency for food trucks to avoid recently visited locations is strong evidence for consumer taste-for-variety. This interpretation is robust to a variety of alternative explanations, such as learning or time-varying demand.

We conclude our paper by demonstrating that the increase in variety due to food truck mobility is substantial. For the ten most popular food truck locations in our data, we find that the average number of trucks visiting each location per week is 23.4 while the average number of brick-and-mortar restaurants within walking distance of these locations is 42.3. Food truck mobility contributes significantly to the increase in restaurant variety: in a counterfactual where trucks are forced to choose a location permanently, each location will have on average only 15.8 food trucks.

Our paper contributes to two strands of literature in urban economics. The first is the literature on the consumption benefits to urban density, among which is greater access to product variety, as discussed in a seminal paper by Glaeser, Kolko, and Saiz (2001).[2] Assuming that food trucks could not be profitable in non-urban settings (because, for example, transportation costs are too high), then our results highlight a new way in which product variety is being increased in cities. The increase in variety generated by restaurant mobility does not actually require an increase in retail space, and so our results suggest one way in which even congested cities can continue to increase access to variety. The second strand is the literature on whether information technology is a substitute or complement for cities, a question posed in Gaspar and Glaeser (1998) and further studied in Sinai and Waldfogel (2004). Our results show how IT can be a complement to cities by mitigating the effects of congestion. In particular, we show how food trucks use IT to overcome the locational

[2]Other related studies include Waldfogel (2003), Berry and Waldfogel (2010), Lee (2010) and Couture (2013).

uncertainty caused by urban problems such as traffic and parking difficulty. Interestingly, our paper connects these two literatures by showing how IT acts as a complement to cities through the consumption variety channel.

Our paper also contributes to the literature that studies how advancements in IT affect the information structure of various markets. Jensen (2007) shows how mobile phones relaxed information frictions and increased social welfare in the South Indian fishing market by allowing fishermen to coordinate on sales while at sea. Our results provide an example of how mobile technology can have such positive spillover effects even in developed markets where information was already disemminated quite efficiently before mobile technology. Brynjolfsson, Hu, and Smith (2003) study how the internet has affected the market for books, which is another example of a market in which IT has increased access to variety. Other related studies include Anderson and Magruder (2012), a study of online restaurant reviews and the restaurant industry; Kroft and Pope (2013), a study of the effect of Craigslist on housing and labor markets; Aker (2010), a study of the effect of mobile phones on price dispersion in agricultural markets; and Brown and Goolsbee (2002), a study of internet price competition in the life insurance market.

Methodologically, our paper is closest to Kearney and Levine (2014), who use both Google and Twitter data to study media influence on teen fertility decisions. Both Kearney and Levine (2014) and our paper contribute to a growing body of research that uses rich new data sources from the internet to answer interesting economic questions. For example, Da, Engelberg, and Gao (2011), Markellos and Vlastakis (2012), and Stephens-Davidowitz (2013) use Google search activity as proxies for variables that are difficult to measure, as we do in this paper. Choi and Varian (2009b,a); Choi and Liu (2011) and Chauvet, Gabriel, and Lutz (2013) show the utility of using Google Trends in economic forecasting for a variety of markets, from the labor market, to tourism, to housing, respectively.

2 A theory of food trucks

Model overview

The goal of the modeling exercise is to illustrate in a simple way how mobile communication technology can enable the food truck industry and thereby increase access to food variety. In the model, a restaurant owner decides either to operate as a food truck, which allows him to serve different locations day-to-day, or to operate as a brick-and-mortar shop, which ties him to a single location. The benefit to being able to serve different locations is that consumers have a taste-for-variety in their day-to-day food consumption and so the food truck can avoid customers which have already been served recently. The cost to being a food truck is that there is uncertainty as to whether a location will be accessible on any given day. For example, all the parking spots at a location may be taken before the food truck can arrive. We abstract from other differences between operating as a food truck or as a brick-and-mortar, such as cost differences, to focus on the model's qualitative predictions about taste-for-variety and the role of mobile technology.[3]

Without mobile communication, the locational uncertainty reduces consumer demand because the consumer must pay an inspection cost (going outside) before learning whether the food truck is at his location or not.[4] The introduction of mobile communication technology allows the food truck to broadcast its location in real-time to the consumer. The consumer will therefore know whether or not the food truck is at his location before going outside.

[3]Another mechanism through which mobile technology can increase food truck profitability is by helping trucks to coordinate on their location decisions. Although we did not find direct evidence of coordinating behavior, neither can we rule this out as a possibility. Nevertheless, our empirical evidence will strongly suggest that both locational uncertainty and taste-for-variety are important mechanisms, regardless of whether coordination is present as an additional mechanism.

[4]It is possible that if there are already many food trucks in operation, then the effects of uncertainty on consumer demand may be smaller, as the consumer may just go outside assuming that at least one truck he likes will be available. However, as we show below, gourmet food trucks really did not exist prior to smartphones and social media. Our model therefore focuses on the case where the industry is not already mature and where the information costs may be large.

For reasonable parameter values, we show that this technological innovation has an enabling effect on the food truck business model, pushing its profitability from below brick-and-mortar to above brick-and-mortar.

Operating as a brick-and-mortar

Consider the decision of a single restaurant deciding whether to be a food truck (FT) or a brick-and-mortar (BM). There are two identical locations each with a unit mass of consumers. Consumers are tied to their location, which reflects the fact that consumers face significant travel costs (i.e. office workers going out to lunch). In each period, consumers decide whether to go outside to visit the restaurant, or to consume an outside option with utility normalized to zero. The utility that consumer i receives from visiting the restaurant at time t is given by:

$$u_{it} = u_0 - \beta d_{i,t-1} - \epsilon_{it}$$

where d_{it-1} is an indicator for whether the consumer visited the restaurant last period and ϵ_{it} is an idiosyncratic component that is i.i.d. over time and over consumers, distributed according to the c.d.f. F.

If the restaurant is brick-and-mortar, then there is no uncertainty as to whether the restaurant will be there when the consumer goes outside. The cost of going outside is K, and so the expected demand at time t is:

$$\begin{aligned} Q_t^{BM} &= \int_i [u_0 - \beta d_{i,t-1} - \epsilon_{it} - K \geq 0] \, di \\ &= Q_{t-1}^{BM} F(u_0 - K - \beta) + \left(1 - Q_{t-1}^{BM}\right) F(u_0 - K) \end{aligned}$$

In the steady state, demand is given by:

$$Q^{BM} = \frac{F(u_0 - K)}{1 + F(u_0 - K) - F(u_0 - K - \beta)}$$

If we normalize profits per customer to 1, then the steady state profit each period is simply equal to the demand:

$$\Pi^{BM} = Q^{BM} = \frac{F\left(u_0 - K\right)}{1 + F\left(u_0 - K\right) - F\left(u_0 - K - \beta\right)} \tag{1}$$

Operating as a food truck

If the restaurant operates as a food truck, it may choose a different location each period. It begins the period by announcing an intended location, call it j, and consumers at both locations observe the announcement. After the announcement, each location becomes inaccessible to the food truck with probability λ. The accessibility shock is assumed to be independent across locations. If the announced location is accessible, the food truck will visit it; otherwise it will visit the alternative location k if k is accessible but j is not. If both locations are inaccessible, the food truck does not operate that period.

When there is no mobile communication, we assume that the consumer has to pay the cost K of going out before knowing the realization of λ. If a consumer goes outside and the truck is not there, he consumes the outside option. A consumer's expected utility to going out at the announced location j is therefore:

$$V_{ijt} = (1 - \lambda)\, u_{it} - K$$

and the demand at the announced location j is:

$$\begin{aligned} Q_{jt}^{FT} &= \int_i \left[(1 - \lambda)\left(u_0 - \beta d_{i,t-1} - \epsilon_{it}\right) - K \geq 0\right] di \\ &= Q_{jt-1}^{FT} F\left(u_0 - \frac{K}{1-\lambda} - \beta\right) + \left(1 - Q_{jt-1}^{FT}\right) F\left(u_0 - \frac{K}{1-\lambda}\right) \end{aligned}$$

Because of taste-for-variety, the truck's optimal strategy is to change locations each period. So j is the announced location only if $Q_{jt-1}^{FT} = 0$ and Q_{jt}^{FT} simplifies to:

$$Q_{jt}^{FT} = F\left(u_0 - \frac{K}{1-\lambda}\right)$$

At the unannounced location, k, a consumer's utility to going out is given by:

$$V_{ikt} = \lambda\left(1-\lambda\right)u_{it} - K$$

Demand at the unannounced location is therefore:

$$Q^{FT}_{kt} = Q^{FT}_{kt-1}F\left(u_0 - \frac{K}{\lambda\left(1-\lambda\right)} - \beta\right) + \left(1 - Q^{FT}_{kt-1}\right)F\left(u_0 - \frac{K}{\lambda\left(1-\lambda\right)}\right)$$

In the Appendix, we characterize the full steady-state solution for the quantity demanded (and profit) Q^{FT}. For ease of exposition and to build the key intuition, in the main text we present a first order Taylor approximation of the full solution around $\lambda = 0$:

$$\Pi^{FT} = Q^{FT} = \left(1-\lambda\right)F\left(u_0 - K\right) - \lambda K f\left(u_0 - K\right) \tag{2}$$

where f is the p.d.f. of F. The first term in (2) can be thought of as the probability of the preferred location being accessible multiplied by demand at that location under no uncertainty. The second term is the penalty to demand coming from consumer uncertainty about whether the truck will be at the announced location or not. Terms related to demand from the unannounced location disappear in the first-order approximation because the uncertainty cost $K/\lambda\left(1-\lambda\right)$ is too high—very few consumers are going to go out at the unannounced location because the food truck is unlikely to visit it.

When comparing Π^{BM} to Π^{FT}, note that if $\lambda = 0$ and $\beta > 0$, then $\Pi^{FT} > \Pi^{BM}$. Food truck dominates brick-and-mortar in this case because the food truck can alternate between locations each period, capitalizing on the consumers' taste-for-variety without facing a reduced market due to location uncertainty. However, for $\lambda > 0$ the comparison between Π^{BM} and Π^{FT} is ambiguous—there is always a λ large enough such that $\Pi^{FT} < \Pi^{BM}$.

The effect of mobile communication technology

Mobile technology allows the food truck to broadcast its location in real-time, so that consumers at both the announced and unannounced locations know the realization of λ before paying the inspection cost. Therefore, at whichever location the food truck ultimately visits, the consumer's utility to going out becomes:

$$V_{it} = u_{it} - K$$

and expected demand at the visited location l is:

$$Q_{lt}^{FT,MC} = Q_{lt-1}^{FT,MC} F\left(u_0 - K - \beta\right) + \left(1 - Q_{lt-1}^{FT,MC}\right) F\left(u_0 - K\right)$$

If the visited location is the announced location j then quantity demanded is:

$$Q_{jt}^{FT,MC} = F\left(u_0 - K\right)$$

If the visited location is the unannounced location k then quantity demanded is:

$$Q_{kt}^{FT,MC} = Q_{kt-1}^{FT,MC} F\left(u_0 - K - \beta\right) + \left(1 - Q_{kt-1}^{FT,MC}\right) F\left(u_0 - K\right)$$

The first order approximation of the steady state expected quantity demanded is:

$$\begin{aligned}
\Pi^{FT,MC} &= Q^{FT,MC} \\
&= (1-\lambda) F\left(u_0 - K\right) \\
&\quad + \lambda \Big[1 + F\left(u_0 - K - \beta\right) - F\left(u_0 - K\right)\Big] F\left(u_0 - K\right) \qquad (3)
\end{aligned}$$

When comparing equation (3) with equation (2), it is easy to see that $\Pi^{FT,MC} > \Pi^{FT}$ for all values of λ, β and K. The first term in (3) is identical to the first term in equation (2). The second term in equation (2) does not appear in (3): there is no demand penalty due to uncertainty in (3) because consumers can observe the realization of λ before deciding whether to go out. Therefore, mobile communication increases demand at the announced location. The second term in (3), which is always positive, is the probability that the preferred location is inaccessible, but the non-preferred location is accessible, multiplied by the quantity demanded at the non-preferred location. Without mobile communication, this term disappeared because demand is negligible at the unannounced location. The second term in (3) therefore illustrates a second benefit that mobile communication confers upon food trucks: it increases demand at the unannounced location in the event that a truck needs to deviate from its announced location. Demand is increased at the unannounced location because mobile technology allows the truck to communicate to consumers that it will be at the unannounced location, after uncertainty is realized. Finally, we also note that in our simple model, quantity demanded is a sufficient statistic for total surplus, and so enabling food trucks increases welfare.

Figure 2 shows a phase diagram indicating the values of λ and β for which either it is always more profitable to be a food truck, always more profitable to be a brick-and-mortar, or when the introduction of mobile communication has an enabling effect on the food truck business model. The parameters used to generate Figure 2 are: $u_0 = 0.5$, $K = 0.05$, and $\epsilon_{it} \sim U[0, 1]$. The model is simulated using the full steady-state solution rather than the first-order approximation, so the results are valid even for large λ. The figure shows that when λ is low and β is high, it is always more profitable to be a food truck. When β is low and λ is high, then it is always more profitable to be a brick-and-mortar. For intermediate levels of β and λ, the introduction of mobile communication has an enabling effect on the food truck business model, pushing its profitability from below brick-and-mortar to above brick-and-mortar. To the extent that restaurants are associated with heterogeneous β's, the theory allows for the realistic possibility that some food trucks did exist before mobile technology and at the same time the existence of others trucks is directly facilitated by mobile technology.

3 The empirical link between food trucks and mobile technology

We now present evidence in support of our model's prediction that the rise of the food truck industry is related to the rise in mobile communication technology. Our empirical strategy exploits within MSA variation in the timing of mobile communication proliferation. Different regions of the country experienced this technology growth at different times and at different rates for reasons that are plausibly unrelated to food truck growth, such as timing in the construction of 3G-capable base-stations and the market shares of carriers selling 3G-capable smartphones.

3.1 Data

Given the absence of MSA-level data on direct measures of mobile communication proliferation and real food truck activity, we use data from Google Trends (http://www.google.com/trends/). We downloaded a panel dataset on Google search volume for terms related to food trucks and for terms related to smartphones and social media (henceforth S&S).[5] These data are useful because if the food truck industry is growing, we should observe an increase in the number of Google searches for food trucks as consumers search online to learn about reviews, menus, prices, locations, etc, for trucks serving in their area. Likewise, growth in access to mobile communication devices and social media should be associated with an increase in Google searches for S&S terms, as consumers search online for product and price information, and for specific social media sites, like Twitter.

For each time period t and for each geographic unit i, Google Trends provides an index y_{it} measuring the popularity of a particular search term relative to all other Google searches by users in that geographic unit in that time period. In our main specifications, we use MSAs – which is the finest level of geographic detail available – as our geographic unit and quarter as our time unit.[6] The data are normalized so that within each MSA, y_{it} takes the value

[5]Search terms related to smartphones and social media include “3g”, “smartphone”, “iphone”, “android”, “4g” and “twitter”. Search terms related to food trucks were simply “food truck”. We included variations of compound words with alternative spacing and hyphenation.

[6]The Google Trends data can only be downloaded at the weekly level. We aggregate the data to the MSA-quarter level by taking the median index value over the weeks in each MSA-quarter.

of 100 in the week where the search term was most popular relative to other weeks in that MSA. If $y_{it} = 50$ and $y_{i,t+1} = 55$, this would imply that the search term was 10% more popular in MSA i in week $t+1$ than in week t. The data are not comparable across MSAs because the normalization occurs within MSAs. As a result, our main regressions below include MSA fixed effects and use within MSA variation in search intensity.

3.2 Results

We first explore the search trends at the national level and then move to our main specifications, which explore the trends at the MSA level. Figure 3 shows that interest in food trucks is strongly related to interest in S&S at the national level. The explosion in search activity for food trucks following the introduction of S&S is mostly consistent with the revenue data presented in Figure 1.[7] One difference is that internet searches for food trucks were very low before mobile technology whereas the revenue data show that industry revenue was still sizeable.[8] One possible explanation is that some mobile trucks were able to operate profitably pre-technology despite the difficulty of making their real-time location decisions searchable online. In our model from Section 2, these would have been restaurants who serve food types for which taste-for-variety is especially high (e.g. an ice cream truck).

Figure 3 also plots the time series for searches on restaurants, which does not appear to be related to interest in either S&S or food trucks. This suggests that the relationship between food trucks and mobile technology is not reflecting an underlying trend in the food service industry, but rather something unique about food trucks. [9]

[7] One may wonder why food trucks only took off with smartphones when other forms of mobile communication, such as text messaging, had been available years before. The key feature of smartphones is that they allow mobile internet access and access to social media applications, which are less cumbersome than text messaging for the purpose of reaching a large, unspecified audience, and for the purpose of transmitting longer forms of media, such as pictures and restaurant reviews.

[8] A Google Trend value of zero means that search volume is below some threshold and does not necessarily imply that there is literally zero search volume.

[9] We can also rule out the possibility that growth in food truck interest is due to changes

We next turn to our main results, which explores search trends at the MSA level for each of the 100 largest MSAs in the U.S.[10] We run variations of the following linear regression:

$$foodtruck_{it} = \alpha_1 \times S\&S_{it} + \alpha_2 \times (S\&S_{it}) \times (poprank_i) + \beta X_{it} + \gamma_i + \delta_t + \epsilon_{it}$$

where $foodtruck_{it}$ ($S\&S_{it}$) is the value of the search index for food trucks (S&S) in MSA i quarter t. We interact S&S search volume with the city's population rank because it is possible that smaller cities do not have the population to support a food truck industry, even if mobile technology is prevalent. The remaining right hand side variables reflect observable controls, MSA effects, and time effects respectively; the inclusion of these variables will vary by specification.

Table 1 presents the results of these regressions. Column 1 of Table 1 presents the results with MSA fixed effects and seasonal controls (i.e. a dummy for each calendar quarter). For a large city like New York or Los Angeles, our results imply that a one unit increase in the search volume index for mobile communication corresponds to over a 0.8 unit increase in the search volume index for food trucks, which suggests a strong relationship between mobile communication proliferation and food truck growth. If we strip out aggregate time series trends by including year fixed effects, the effect is attenuated but still highly significant, as shown in column 2 of Table 1. Columns 3 and 5 present the results when we add city-by-year demographic and economic controls from the County Business Patterns census data.[11] There is still a strong relationship between food truck and S&S searches, and when we restrict the specification in column 2 so that the sample includes only years where our

in food attitudes. Figure 4 shows that searches for "gourmet" and "organic" stayed roughly flat. In currently unreported results, we also find that searches for terms related to "do-it-yourself" cooking such as "home cooking", "food network", "chef" also stayed roughly flat.

[10] The estimation sample will include only 54 cities because only 54 cities had enough search volume for food trucks for Google Trends to provide the data.

[11] We include average age of the population, percent white, percent male, average income, unemployment rate, percent with college degree, and total population.

control variables are available, we find that adding the control variables does not change the coefficient of interest. This gives us confidence that adding additional omitted variables would not overturn our main result on the close relationship between foodtruck and S&S related searches.

Since our sample includes multiple years of data, we can run a test for causality in the spirit of Granger (1969), as discussed in Angrist and Pischke (2008) and applied in Autor (2003). The idea is that if S&S growth causes an increase in food truck growth, then we should expect the relationship between S&S searches and food truck searches to be strongest when S&S searches are lagged. After all, we would not expect food trucks to begin operating immediately once the technology is in place to facilitate their business model; we expect that it should take some time for restauranteers to recognize the effects of the new technology, and some time for them to set up their businesses and overcome startup costs. Furthermore, future values of S&S searches should not have an effect on current food truck searches, all else equal. This discussion motivates the specifications presented in Table 2, which adds one and two year lagged and forward values of $S\&S_{i,t}$ to the specifications run in Table 1. The estimates show that the effect of $S\&S_{i,t}$ is strongest when it enters with a two year lag, and the effects of forward values of $S\&S_{i,t}$ are substantially smaller and statistically insignificant in most of the specifications. This pattern is consistent with a causal interpretation of the correlations between $S\&S$ and foodtrucks.

Finally, Table 3 shows the regression results when we consider the effects of smartphones and social media separately. Interestingly, the separate effect of smartphones and social media are statistically insignificant by themselves (although precision is an issue), but the interacted effect is positive and significant. This result is consistent with the theory that both the hardware (smartphones) and the software (social media) have to be in place in order for mobile technology to overcome the information friction in our theory.

4 The Washington D.C. food truck market

The previous section documents evidence for the main prediction of our model: that introduction of mobile technology will facilitate the growth of food trucks. The evidence provided, however, is silent on what mechanisms could generate this link. We now turn to directly testing the specific mechanisms in our model—locational uncertainty and taste-for-variety. To test for these mechanisms, we use rich and novel micro-datasets on food trucks operating in the Washington D.C. metro area. Before turning to the specifics of the data and analysis, we first provide a brief description of the Washington D.C. food truck market.

The Washington D.C. metro area is one of the largest markets for food trucks in the U.S. Relative to population, the D.C. metro area generates the fourth most google searches for food trucks; the top seven cities are Los Angeles, San Diego, Orlando, DC, San Francisco, Raleigh-Durham, and Miami. According to FoodTruckFiesta.com, there are (as of December 2013) 204 active food trucks operating in the Washington D.C. metro area.

There are several unique features of the D.C. food truck market that make it ideal for our study. First, Washington D.C. has a dominant aggregator website, FoodTruckFiesta.com, which centralizes information about the universe of food trucks operating in the metro area. Because there is a single dominant website, the collection of the daily location decisions for the universe of food trucks is a simple and standardized task. Second, the primary market for food trucks in D.C. are office workers going out to lunch. Thus, the market is roughly consistent with two assumptions that we use in our theory—that consumers are fixed to their location and that the distribution of consumers at each location is the same each day. Third, D.C. food trucks tend to cluster along a couple of blocks outside large employment centers rather than spreading out over multiple surrounding blocks (as in Los Angeles, for example). This makes the behavior of D.C. food trucks amenable to a tractable discrete choice model of location decisions. Fourth, according to FoodTruckFiesta.com, about 90 percent of D.C. food trucks have Twitter accounts, and the large majority of these use Twitter to broadcast their daily location decisions. We can therefore be confident that our results, which are based on truck tweets, are representative of the entire food truck industry in the D.C. metro area.

5 Direct evidence for locational uncertainty

To test for the presence of locational uncertainty, we obtained the entire history of Twitter feeds for 200 trucks that actively operate in the Washington D.C. metro area and use Twitter.[12] We downloaded the Twitter data using software provided by Next Analytics Corporation. The data contains a total of 189,550 tweets, with the first being posted on September 21st, 2009 and the last being posted on November 20th, 2013. In addition to the content of a tweet, we observe the exact date and time it was posted. Many tweets contain information regarding the food truck's location that day, and some also contain information indicating an unexpected change of plans.

To formalize the extent to which tweets contain location information, we parse the data to identify tweets announcing the location of the posting truck.[13] Summary statistics are presented in Table 4. We find that out of 189,550 tweets, 71,777 (38 percent) contain location information. Out of an average of 3.5 tweets per truck per weekday, we find that the average number of location-related tweets is 1.4. The average truck posts at least one location-related tweet on about 69 percent of the days in which it tweets at all.This is strong evidence that food trucks use social media to communicate their location, but it does not necessarily indicate the presence of locational uncertainty. It is possible, for example, that social media is used simply to remind customers about a previously announced schedule.

To obtain stronger evidence that locational uncertainty is a factor, we further parse the data to identify tweets indicating an unplanned change of

[12]Twitter is a website that allows users to post short messages (called tweets) that are publicly viewable by anyone with an internet connection; a Twitter feed is the entire history of messages that a user has posted. See Figure 5 for a sample of the Twitter data.

[13]We identify location-related tweets by parsing the text for known location and street names. The data and parsing algorithms are available from the authors upon request.

schedule. These tweets are identified based on statements about the unavailability of parking, statements about change of plans, statements warning that the truck will be late to arrive at a previously announced location, and statements about unpredicted mechanical failures or maintenance. We find that 2.3 percent of all tweets indicate an unexpected change of plans. Out of an average of 3.5 tweets per truck per weekday, the average number of these uncertainty-related tweets is 0.08. This implies that the average truck posts at least one uncertainty-related tweet on over 7 percent of the days in which it tweets at all. From the perspective of the consumer, this is a significant source of uncertainty. Assuming that every day in which a truck tweets is a day in which it operates, the data imply that there is about a 1 in 13 chance that a desired truck is not at its expected location at the expected time. The implied level of uncertainty increases if one assumes that trucks tweet even on days in which they do not operate.

The facts presented above show that food trucks use social media to communicate the realization of locational uncertainty and that the degree of locational uncertainty is significant. To further show that the *real-time updating* of locational uncertainty is important (and hence, that smartphones, which allow trucks to communicate with customers from the road, are important), we plot the time distribution of location-related tweets and the distribution of uncertainty-related tweets in Figure 6. Figure 6 shows that location-related tweets occur slightly earlier in the day than uncertainty-related tweets. Additionally, uncertainty-related tweets exhibit a much larger density during lunch hours (12:00pm to 1:00pm) than location-related tweets, suggesting that unplanned changes of schedule often occur at the last minute. The last-minute nature of these tweets suggests that the real-time broadcast of location information through smartphones and social media is an important tool that food trucks use to reduce the uncertainty faced by consumers.

Although we have only collected Twitter data for food trucks in Washington D.C., we can provide suggestive evidence that locational uncertainty is important in other markets as well. To do this, we perform a Google search for "[MSA name] food trucks" for the ten largest MSAs in the U.S. Table 5 shows the fraction of the results that link to a location aggregator, out of the top 10, top 3, and top 1 returned results.[14] In most of the cities, Google returns a location aggregator as the number one search result. Because Google returns its search results by order of popularity, the results in Table 5 suggest that many people who search for food trucks are looking for information about food truck locations, and this effect is not limited to any one particular city.

We have documented three facts using the Twitter data that are all consistent with our model of locational uncertainty. First, locational uncertainty is a significant friction faced by food trucks. Second, food trucks use Twitter to inform consumers about the realization of locational uncertainty. Third, food trucks update consumers in real time. Combined with the results in section 3 showing the correlation between S&S searches and food trucks, the evidence is substantial that mobile communication technology plays an important role in reducing frictions related to locational uncertainty in the food truck industry.

6 Evidence for taste-for-variety

6.1 Food truck location data

In this section, we provide empirical support for another key hypothesis of our model: that food trucks use their mobility to avoid recently visited locations, thereby capitalizing on consumer taste-for-variety. We collected data on D.C. food truck location decisions by writing a computer program to automatically extract information from daily emails sent by FoodTruckFiesta.com. The emails have a consistent, easy to process format. The emails contain information about the daily lunchtime locations of each food truck in the D.C. metro area, as well as some basic information about each truck, including their name and cuisine type. We also recorded each day's high temperature and chance of rain from accuweather.com.

During our sample period, 204 food trucks were in operation. Table 6, panel

[14] A location aggregator is a website that collects real-time information about food truck locations in its area and displays them on a single site.

A summarizes some basic information about the food trucks. The majority of food trucks were already open at the start of our sample on May 2nd, 2012. The majority of food trucks also operated through the entire sample period: over half of the food trucks were last observed operating on March 28, 2013 or later (our sample ends on March 29, 2013). Food trucks were observed to operate an average of 80 days over our sample period, which on average is 37% of the days between each truck's first and last observed operation dates. This calculation includes weekends even though our data does not allow us to see food truck activity on weekends. If weekends are omitted, the average food truck operates 50% of the days between its first and last observed operation dates. This suggests that the decision of whether or not to operate on a given a day is a non-trivial decision for food truck owners.[15]

There are 70 unique locations in the data, with the three most popular being L'Enfant, Farragut Square, and Metro Center. The average food truck visited just under 8 locations in our sample period, with 93% of the trucks visiting at least 2 locations. Over half visited more than 8 locations, and the largest number of distinct locations visited was 37. We explore the diversity in location choices among food trucks further in Figures 7, 8 and 9. These figures plot different measures of how concentrated the trucks' location choices are. The figures show that although there is a tendency for trucks to follow fixed weekly schedules, there is still enough variation in each trucks' day-to-day and week-by-week location choices for us to conclude that they are actively making decisions about where to locate each day.

6.2 Location choice model

We now introduce a model of food truck location choice that can capture the effect of taste-for-variety. Each day t, food truck i chooses between operating in locations $j = 1, \ldots, J$ or not operating ($j = 0$). The profit that food truck

[15] Many food trucks do not operate every day because it is not a full-time job for some owners. On days where demand is expected to be low, such as when it is raining, a food truck may not find it worthwhile to operate.

i expects to receive from location $j = 1, \ldots, J$ is given by:

$$\pi_{ijt} = X_{ijt}\beta + \sum_{l \in \mathcal{L}} \delta_l L_{lijt} + \alpha \sum_{l=\{7,14,21\}} d_{ij,t-l} + \sigma\left(\epsilon_{ijt} - \epsilon_{i0t}\right)$$

and the profit to not operating is given by:

$$\pi_{i0t} = 0$$

L_{lijt} is an indicator for whether truck i operated in location j any time in the past l days and d_{ijt} is an indicator for whether truck i operated in location j in day t. The set of lags $\mathcal{L}$ that we used were $\mathcal{L} = \{1, 2, 3, 4, 5, 6, 14, 21\}$; that is, we compute separate effects for the truck having operated in the same location within the past 1, 2, 3, 4, 5, 6, 14, and 21 days. The total effect of having operated in a location one day ago is therefore the sum of all δ_l for $l \in \mathcal{L}$, while the total effect of having operated in a location not one, but two days ago, is the sum of all δ_l for $l \in \mathcal{L} \setminus \{1\}$.[16] We included separate effects for the truck having operated in the location exactly 7, 14, or 21 days ago (i.e. the $d_{ij,t-l}$'s) in order to capture the tendency of many trucks to follow weekly schedules. X_{ijt} is a vector of observable controls. In our main specification, X_{ijt} includes an indicator for whether it was raining or snowing on day t, an indicator for whether the high temperature for the day was less than 50F, and an indicator for whether day t is before or after the imposition of a 10% sales tax which took effect on October 1st, 2012. We will also experiment with various fixed effects for (i) each location (ii) each foodtruck (iii) each weekday.[17] The error term, ϵ_{ijt}, is assumed to be iid across i and t but not across j. Within i and t, ϵ_{ijt} follows a standard nested logit structure as described in Train (2009), with scale parameter σ. The "inside options", $j = 1, \ldots, J$, are in one nest with

[16] We have also estimated a richer specification with a separate effect for every lag from 1 to 21. The results do not change much because the taste-for-variety effect turns out to last no longer than a week.

[17] We ignore any possible agglomeration or competition effects in the location choice model. We do not expect this omission to bias our estimates of taste-for-variety. Indeed, when we include the observed number of trucks in each location as a proxy for competition/agglomeration, our estimates of taste-for-variety are little changed.

nesting parameter λ, and the "outside option", $j = 0$, is in the other nest. This structure is appropriate for our context because reasons which would cause a food truck to choose to operate in one location over not operating can be correlated with reasons which would cause a food truck to operate in another location over not operating.

Each day, truck i chooses the option j to maximize π_{ijt}. For $j = 0, \ldots, J$ let us define $v_{ijt} = \frac{1}{\sigma}\pi_{ijt} - \epsilon_{ijt} + \epsilon_{i0t}$ as the expected profits less the error term, and normalized by the scale parameter. For locations $j = 1, \ldots, J$, the probability that truck i chooses to operate in j (taking expectations over ϵ_{ijt}) is:

$$P_{ijt} = \frac{e^{v_{ijt}/\lambda}\left(\sum_{k=1}^{J} e^{v_{ikt}/\lambda}\right)^{\lambda-1}}{1 + \left(\sum_{k=1}^{J} e^{v_{ikt}/\lambda}\right)^{\lambda}}$$

and the probability that the truck chooses to not operate ($j = 0$) is:

$$P_{i0t} = \frac{1}{1 + \left(\sum_{k=1}^{J} e^{v_{ikt}/\lambda}\right)^{\lambda}}$$

Our data allows us to see the location decisions d_{ijt} of each truck i in each day t. We can therefore estimate the parameters of the model (up to the scale normalization) by maximum likelihood. The main parameters of interest are the δ_l's. For each l, δ_l represents the effect on profits from operating in a location you visited at least once in the past l days. If there is taste-for-variety, then we expect δ_l to be negative, especially for small l.

6.3 Results

Table 7 reports the estimation results from the nested logit model. The first column reports baseline results when no fixed effects are included. The addition of fixed effects increases the magnitude of the lag effects in the first week, and reduces the positive effects of having operated in a location two to three weeks ago. It is likely that the positive effect of having chosen a location two or three weeks ago is capturing some unobserved familiarity of certain trucks with certain locations. In column 3 we estimate a specification in which each truck's choice set is restricted to locations that it is observed to have chosen at least once in the data. Once this restriction is made, the positive effect of visiting the same location that was visited two to three weeks ago disappears. Column 4 is identical to column 3, except that the cumulative effects are reported. The estimates in specification 3 reveal that there is a strong negative effect to operating in a location that has been visited recently. The cumulative effect is strongest for a location that has been visited just one day ago, and the strength of the effect decreases as the length of time since the last visit increases. The effect seems to disappear after about a week. The results in Table 7 are consistent with a taste-for-variety that dies out over time. The results in Table 7 also reveal that there is a strong tendency for trucks to visit the locations that they visited exactly 7, 14 or 21 days ago. This positive weekly effect reflects the tendency for trucks to follow weekly schedules.

In order to assess the economic magnitude of our estimation results, we must first estimate the scale parameter, which is not identified from the location data alone. In order to do this, we note that

$$\sigma = \frac{\frac{1}{N}\sum_i \sum_t E\left[\max_j \pi_{ijt}\right]}{\frac{1}{N}\sum_i \sum_t E\left[\max_j v_{ijt} + \epsilon_{ijt} - \epsilon_{i0t}\right]}$$

In words, the formula above says that the scale parameter is equal to the average daily profits measured in dollars, divided by the average value of the normalized profit function used for estimating the choice model. In order to compute the numerator, we use the estimated average daily profit for food trucks in 2012 from Samadi (2012). In order to compute the denominator, we first note that we can write the closed form of the expected maximum over j as:

$$E\left[\max_j v_{ijt} + \epsilon_{ijt} - \epsilon_{i0t}\right] = \log\left[1 + \left(\sum_{j=1}^{J} e^{v_{ijt}/\lambda}\right)^{\lambda}\right]$$

We then compute the average of this value over the trucks and days in our dataset, using the estimated coefficients for v_{ijt} and λ. We end up with a scale parameter equal to 668.92. To get the dollar value of the effect of a unit change in X_{ijt} on π_{ijt}, we multiply the coefficients reported in Table 7 by 668.92.

The estimation results suggest that the magnitude of the taste-for-variety effect is quite significant. Choosing the same location two days in a row results in a $257 loss in the day's profit, which is about 38% of average daily profits. In comparison, the effect of rain or snow is to decrease profits by $179 (26%), the effect of cold weather is to decrease profits by $127 (19%), and the effect of a 10% sales tax is to reduce profits by $207 (31%).

6.4 Alternative explanations

The tendency for food trucks to avoid locations they have visited recently in the past is consistent with a consumer taste-for-variety. In this section, we rule out time-varying demand, food truck learning, and consumer learning as alternative explanations.

One alternative explanation for the results above is that different locations simply have different demands depending on the day of the week. For example, locations near a university may have lower demand on Fridays, while locations near a shopping hub may have higher demand on Fridays. If this were true, then food trucks may change locations day by day simply to follow demand. To rule out this explanation, we re-estimate our preferred specification with location-by-weekday fixed effects.

Second, a truck may avoid visiting the same places in short succession because it desires to learn about the market in a number of different locations. To rule out this explanation, we estimate our model on a sample restricted to trucks with over two months of experience at the start of our sample (this is less than half of the trucks in our sample). Our reasoning is that learning will be less of a motivation for experienced trucks.

A third alternative explanation is that a truck may avoid choosing recently visited places because it can increase consumer awareness by choosing a greater variety of locations. To rule out the consumer awareness explanation, we re-estimate our model on a sample restricted to trucks that are already popular, as measured by having over 1,000 Twitter followers (the median of our dataset). Our reasoning in this case is that trucks which are already well known have less need to increase consumer awareness.

It is possible, however, that trucks that are experienced or popular are so precisely because they avoid visiting the same location too often. It is also possible that all trucks, no matter how experienced or popular, continue to have incentives to visit a variety of locations for the purpose of learning or increasing awareness. To rule out this final possibility, we re-estimate the model on a sample restricted to trucks that have visited less than nine locations in the entire sample. These trucks would appear not to have any motivation for visiting a wide variety of locations to either learn about the market or to increase consumer awareness. If they are indeed popular or experienced, it is not due to their diversity in location choice.

Table 8 reports the results of these robustness exercises. In none of the alternative specifications are the estimated parameters on taste-for-variety changed much. We therefore conclude that the tendency for trucks to avoid recently visited location is better explained by taste-for-variety than any of the above explanations.

6.5 Quantifying the increase in variety

We now perform some simple exercises to calculate the contribution of food trucks to restaurant variety in Washington D.C. A direct measure of the increase in variety would be the amount of unique restaurants that a specific location is exposed to over the course of a week, with and without food trucks. Table 9 computes these measures for the ten largest locations in our data, as measured by total food truck visits. The top ten locations constitute over 75 percent of all food truck visits in the data, and are also among the largest employment centers in the city. Columns 1 and 2 of Table 9 report the count of unique brick-and-mortar restaurants within 4 blocks and 1 mile of each location, respectively, as measured by a search on www.yelp.com for "restaurants" centered at the location. Column 3 counts the average number of unique food trucks that visit the location each week, as computed from our daily location data described above.

Table 9 shows that food trucks generally contribute substantially to the number of restaurants a location is exposed to each week. The average number of food trucks visiting these locations each week is 23.4, whereas the average number of brick-and-mortar restaurants within a 4-block radius of these locations is 42.3. We think of brick-and-mortar restaurants in a 4-block radius as the relevant comparison group because food trucks tend to locate in very close walking distance to each location. Nevertheless, when we use a broader comparison group – the count of brick-and-mortar restaurants in a 1 mile radius, Table 9 shows that the contribution of food trucks to food variety is still significant (23.4/514.9).

Table 9 also shows that mobility is an important mechanism through which food trucks increase access to variety. Column 4 counts the number of food trucks each location would have in a counterfactual world where food trucks choose a location and then are fixed to it.[18] The average number of food trucks each location would have in this counterfactual world is 15.8. The increase in weekly restaurant variety due to mobility is therefore 7.6, or 18% of the average number of nearby brick-and-mortar stores.

The results in Table 9 show that food trucks substantially increase food variety for many consumers and moreover, that mobility contributes significantly to this increase. The latter distinction is important because the increase in variety due to mobility is unique to food trucks. In other words, some of the food trucks could have instead operated as brick-and-mortar, and so the mere existence of these trucks should not be counted as contributing to new variety. The contribution to variety from these trucks' mobility, however, should still be counted.

[18]In the counterfactual, each location is assigned a number of trucks equal to the share of total visits it received in the location data.

7 Conclusion

This paper develops a theory that illustrates two underlying economic forces behind the rapid growth in food trucks: information frictions which are solved by mobile technology, and taste-for-variety. We established three empirical facts to support the theory. First, growing interest in smartphones and social media lead to growing interest in food trucks at the city level, even when controlling for national trends and city heterogeneity. This confirms the broad prediction in our model that mobile technology facilitates the growth of food trucks. Second, food trucks face a significant amount of locational uncertainty and they communicate the realization of this uncertainty in real-time through smartphones and social media. This confirms that locational uncertainty is a significant friction faced by food trucks and that mobile technology helps to relax it. Third, food trucks tend to avoid recently visited locations, even though the distribution of consumers at each location is roughly the same each day. This confirms that food trucks use their mobility to capitalize on consumer taste-for-variety, and that one consequence of the growth in food trucks is an increased access to food variety. We closed the paper by showing that the increase in variety created by food trucks is large.

The results of our paper have implications for how local policymakers should approach the regulation of food trucks. For example, Washington D.C. recently implemented a lottery system whereby the locations that trucks are allowed to visit each day are determined randomly. In our view, this may help ease locational uncertainty, but can be counterproductive in reducing the ability of trucks to serve consumers' taste-for-variety (for example, if two Korean taco trucks are forced to locate in the same place on the same day, or the same truck is forced to locate in the same locations on two consecutive days).

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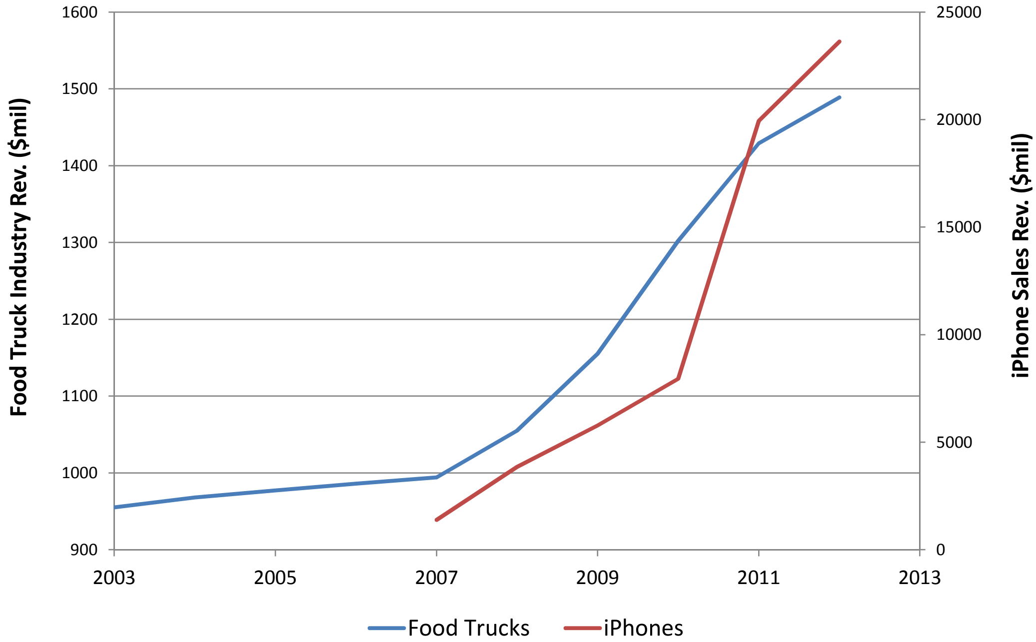
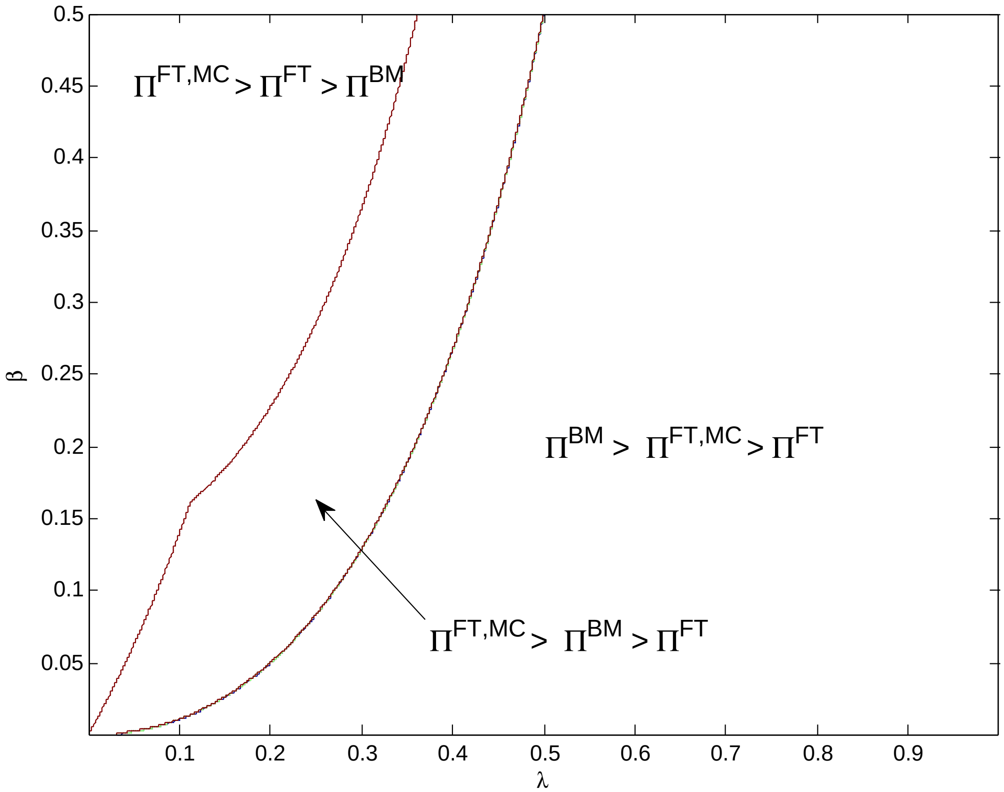
Figure 1: Annual U.S. Food Truck Revenue and iPhone Sales



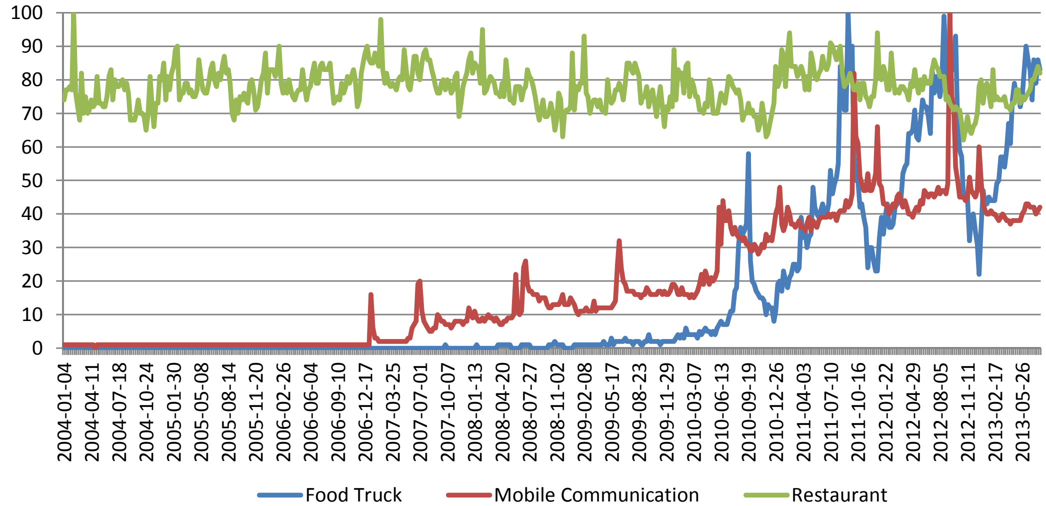
Notes: This figure shows food truck industry revenue and Apple iPhone sales revenues from 2003 to 2012.
Source: Samadi (2012)

Figure 2: Phase Diagram of Food Truck / Brick-and-Mortar Profitability



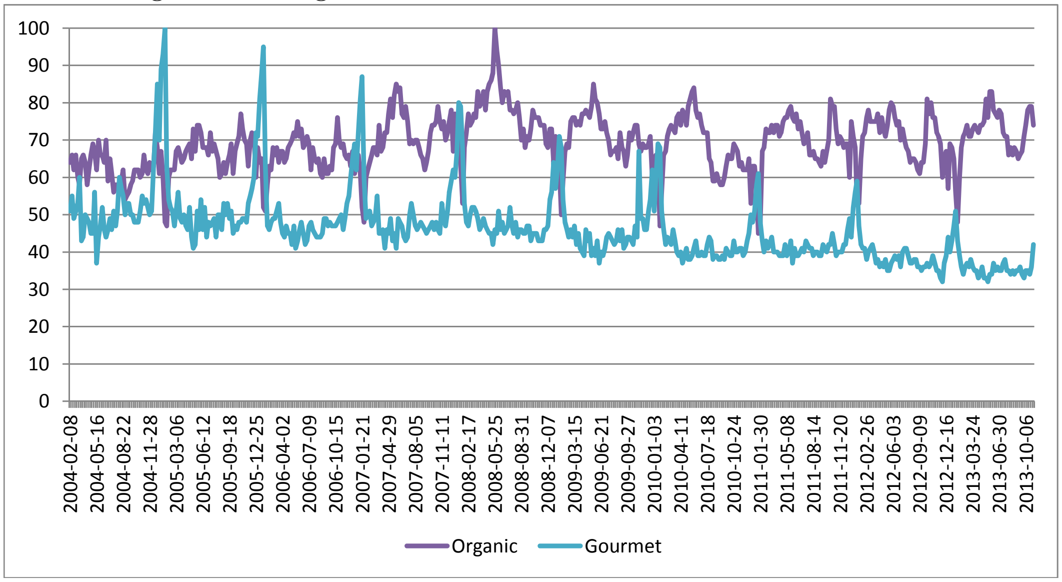
Note: This figure shows simulation results for the two location model described in Section 2 for various values of λ (locational uncertainty) and β (taste-for-variety). ϵ_{it} is distributed uniformly on the unit interval, $u_0 = 0.5$ and $K = 0.05$. For intermediate values of λ and β, mobile communication has an enabling effect on the food truck business model, pushing its profitability above that of brick-and-mortar. For low values of λ and high values of β, it is always more profitable to be a food truck. For low values of β and high values of λ, it is always more profitable to be a brick-and-mortar.

Figure 3: Google Search Trends in the U.S.



Note: Mobile communication search terms include "3g", "smartphone", "iphone", "android", "4g", and "twitter". The data shows no relationship between searches for restaurants and searches for mobile communication or food trucks, but a clear relationship between mobile communication searches and food truck searches.

Figure 4: Google Search Trends in the U.S.: Food Attitudes

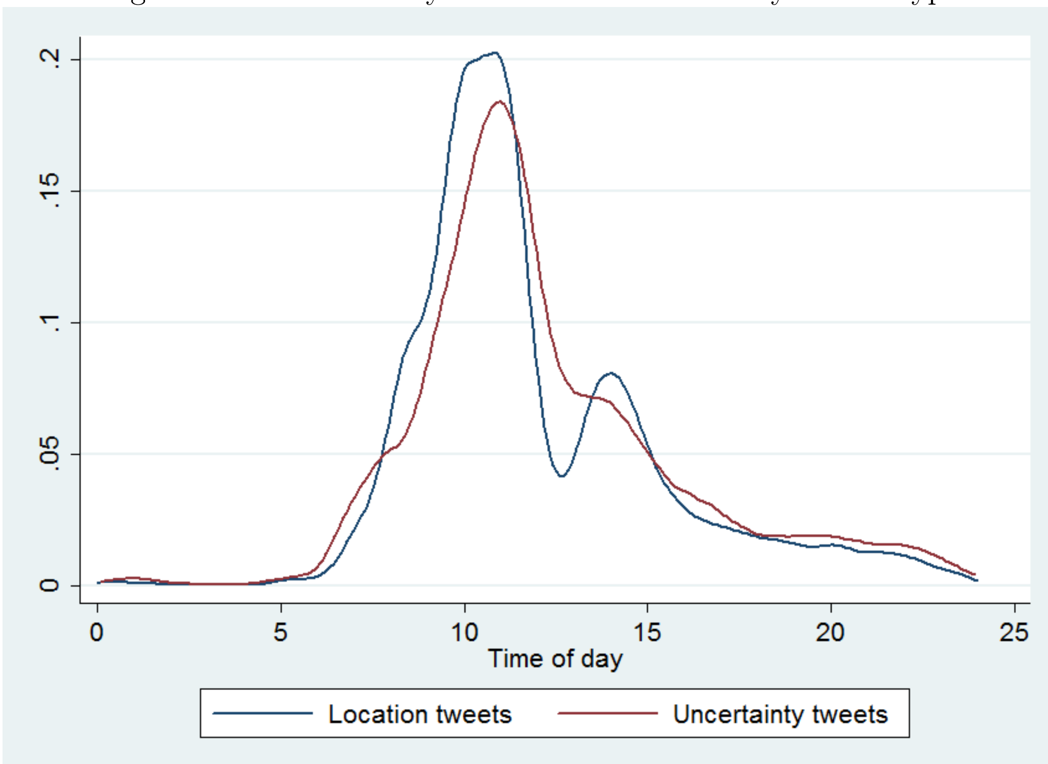


Note: Figure plots Google Trends search intensities for "organic" and "gourmet", respectively. Searches for organic and gourmet show no particular trend nor any correlation to searches for smartphones, social media, or food trucks.

Figure 5: Example of Twitter Data

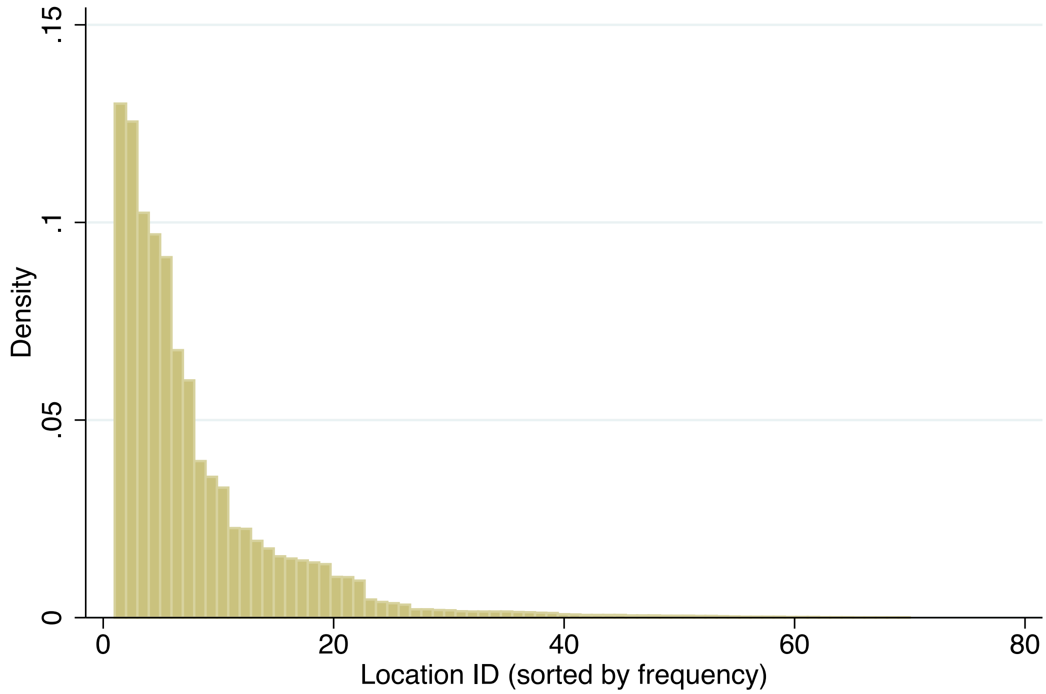
	truck	time	text
5301	BasilThymeDC	31jul2012 08:32:44	'ABCers! WWF people! It's about Basil Thyme you got some Tail! Lobster, that is: We have awesome Lobster & Crab lasagnas 4 U'
5302	BasilThymeDC	31jul2012 08:42:27	To be more clear that's West End 24/25th &M 2day Also the lobster &crab r 2 different lasagnas. Chocolate cannoli.C U soon!
5303	BasilThymeDC	31jul2012 11:37:25	Landed and serving ABC/West End! Come getcha Lobster/Crab on!!
5304	BasilThymeDC	31jul2012 13:08:07	@candycompass no line at Basil Thyme or Chef Driven. What up?!
5305	BasilThymeDC	31jul2012 14:15:36	Farragut- It's never too early to start thinkin It's only 21 hours to Basil Thyme/Lobster Thyme! Asta maÃ±ana!!
5306	BasilThymeDC	01aug2012 08:49:53	Woah! This guys claw's almost as big as mine! Farragut: Time to enjoy Tail + Claws - Fresh lobster- BT style! http://t.co/fCTdwbVH
5307	BasilThymeDC	01aug2012 09:02:37	'Headed to Farragut today! Lobster and Crab - 2 different lssagnas, plus Linda Giuseppe and Catena on board!! C U Soon!'
5308	BasilThymeDC	01aug2012 11:04:39	'Chocolate cannoli, Lobster or Crab lasagnas, Basil Lemonade, 60 second service.. life is good @ Farragut today! C U @ 11:35 :)'
5309	BasilThymeDC	01aug2012 11:14:03	'Metro Center- Tomorrow, we return! Enough of this 'no parking space nonsense. It's time for us to get you back in the game :)!'
5310	BasilThymeDC	01aug2012 11:34:01	Landed and serving @ Farragut. Next to Sang on Wheels and Burritos/Tacos on the sunny side! See u Soon :)
5311	BasilThymeDC	01aug2012 15:48:07	RT @matthewheck: I tried @BasilThymeDC's lobster lasagna today on a whim. Oh.My.God. It's amazing. //Metro Center:your chance 2 try Thurs!
5312	BasilThymeDC	01aug2012 16:13:57	'@timcarman & the reason you weren't eating Lasagna w/ lobster stock, sherry, cream &fresh steamed/shelled by us Tails & Claws instead ...
5313	BasilThymeDC	02aug2012 08:28:11	'It's Frutti de Mer for Metro Centre today: Scallop, Crab or Lobster Lasagnas! Plus traditional, Truffle or Chicken!'
5314	BasilThymeDC	02aug2012 10:02:50	'Apparently Frutti de Mer for Franklin. We tried to stop at 9:28..apparently too early. Got shoo-ed, circled... http://t.co/gnmtIBVK'
5315	BasilThymeDC	02aug2012 10:54:47	'@foodtruckfiesta couldnt park where we said :/ so instead, we r @ Franklin today as usual :)'
5316	BasilThymeDC	02aug2012 11:45:10	'Landed/ serving at Top of Franklin in shade!! Dont Miss our new Scallop, Lobster or Crab lasagnas!! C U soon!'
5317	BasilThymeDC	02aug2012 18:30:01	'@aetherial was Fridays, but im changing it. People afraid 2 try us @US. R 'serve people fast' M.O. betrays us-people go 2 Long lines.*shrug*'
5318	BasilThymeDC	02aug2012 21:54:50	Metro Center - I'm personally driving our spotter car tomorrow. Enough from DPE: its time u got your BT on!!
5319	BasilThymeDC	03aug2012 08:44:08	Taking Two cars to Metro Center to doubly make sure we have delicious Lobster lasagna 4 U today!!
5320	BasilThymeDC	03aug2012 09:43:22	'Metro Center is Beyond Insane to park at.. Two cars, we got ExTrEmEly lucky. In front of Tapas/Mojo, we'll see you at 11:30 Metro Center!'
5321	BasilThymeDC	03aug2012 10:56:24	'Using two resources to park has us a few behind. See you at 11:35ish for Lobster, Crab, Beef, Chicken and Truffle Lasagna!'
5322	BasilThymeDC	03aug2012 11:46:43	Landed & serving at Metro Center!!! Get your lobster/crab on!!
5323	BasilThymeDC	03aug2012 14:03:24	'RT @nicksadoti: Hey @BasilThymeDC, the lobsta lasagna is out of this world. Keep up the good work.'
5324	BasilThymeDC	04aug2012 15:28:27	'@WellsFargo just asked 2 forms of ID,ok, but charged $7.50 to cash a check drawn on THEIR paper&made me THumbprint it like a Criminal #FAIL'
5325	BasilThymeDC	05aug2012 18:20:25	@erinblack3 no worries Erin we'll see you and the whole L Enfant gang for lunch tomorrow!
5326	BasilThymeDC	06aug2012 09:18:20	'L Enfant! Do we even have to tweet today?! You know that Thyme it is by now, don't cha?! :) See you at 11:30!'
5327	BasilThymeDC	06aug2012 10:46:52	'It's almost Basil Thyme L Enfant! Chocolate cannoli, Lobster and crab - 2 different yet Awesome lasagnas+ Linda, Catena+Truffles!'
5328	BasilThymeDC	06aug2012 11:29:16	Landed and serving at L Enfant. We are on 7th next to Halal Grill and Bayou Bros
5329	BasilThymeDC	06aug2012 14:42:27	Thank you L Enfant! See you in a week! State Department- your Basil Thyme is tomorrow! See u then!!
5330	BasilThymeDC	07aug2012 09:21:58	State Department!! It's Basil/Lobster Thyme! Chocolate cannoli See you in T-2 hours!
5331	BasilThymeDC	07aug2012 11:22:26	Landed and serving at State! See you soon!
5332	BasilThymeDC	07aug2012 13:41:32	'Sold out State!! Thank you for coming out! Tomorrow, its Lobster/Basil Thyme for Farragut!! C U soon :)'
5333	BasilThymeDC	07aug2012 15:31:23	'Folks, we are Leveling up! Keep your eyes peeled.. You could grab a Lobster Lasagna for $7, maybe even LESS! RT 4 your buddys :)'
5334	BasilThymeDC	07aug2012 17:52:29	@DCFoodTruckPhot Thank you!
5335	BasilThymeDC	07aug2012 17:56:09	RT @GetKrissed: Went with the crab lasagna for lunch ... Omg @BasilThymeDC it was sooo superb!//TY! Farragut C what the Lob/Crab<3 is about!
5336	BasilThymeDC	08aug2012 08:14:17	''A Lobster lasagna by any other name would smell as sweet' - WS, 1591;'Dang, that Lobster smells awesome!' - You, @ Farragut 2day!'
5337	BasilThymeDC	08aug2012 10:47:58	'Farragut! Lobster. Crab. Truffles. Oh, & the Traditional Beef and awesome Chicken Florentine are no slouches either c u soon!'
5338	BasilThymeDC	08aug2012 11:51:30	Landed and serving at Farragut!! Come get your Lobstah/Crab on!
5339	BasilThymeDC	08aug2012 13:18:56	No line at Farragut! 60 second service means no time to break a sweat...

Figure 6: Kernel Density Plots of Tweet Times by Tweet Type



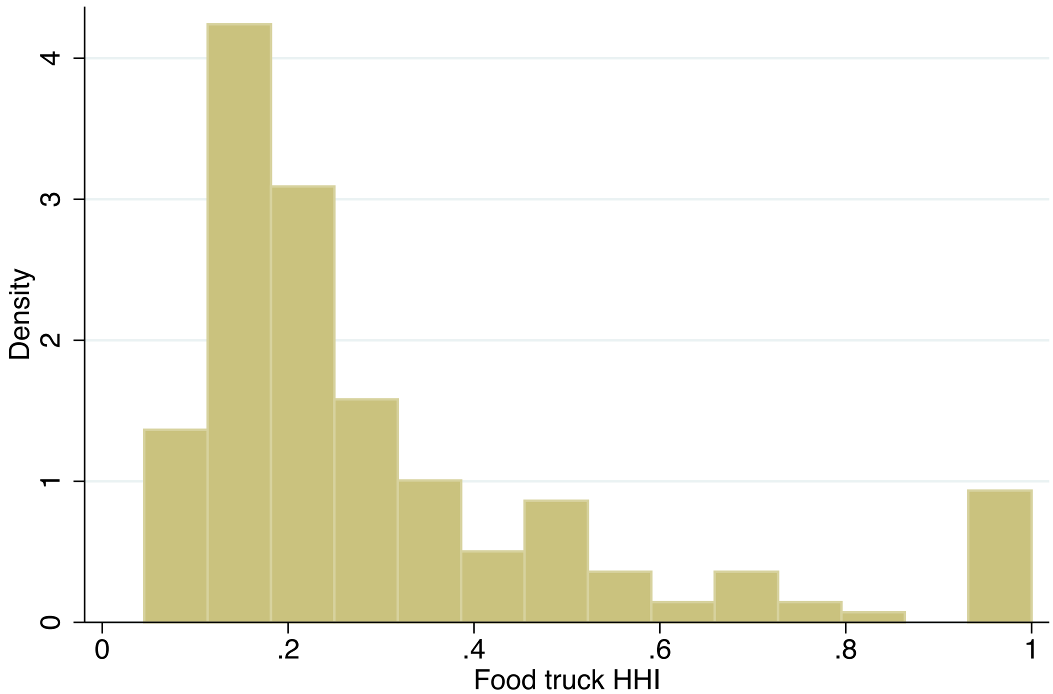
Note: Kernel density plots of tweet times using Epanechnikov kernel with optimal bandwidth. "Location related tweets" are tweets which specify the truck's location. "Uncertainty related tweets" are tweets which indicate a change or delay of plans for the truck, usually due to the inability to find parking or to traffic. Time of day is measured on a 24 hour block so that, for example, a time of day equal to 13 denotes 1:00 pm.

Figure 7: Distribution of Location Choices



Note: This figure plots the distribution of location choices for food trucks in our data. There are 70 locations in total. Although food truck visits are concentrated in about 20 or so locations, the Herfindahl concentration index is quite low at 7.4%.

Figure 8: Distribution of Food Truck Location HHI

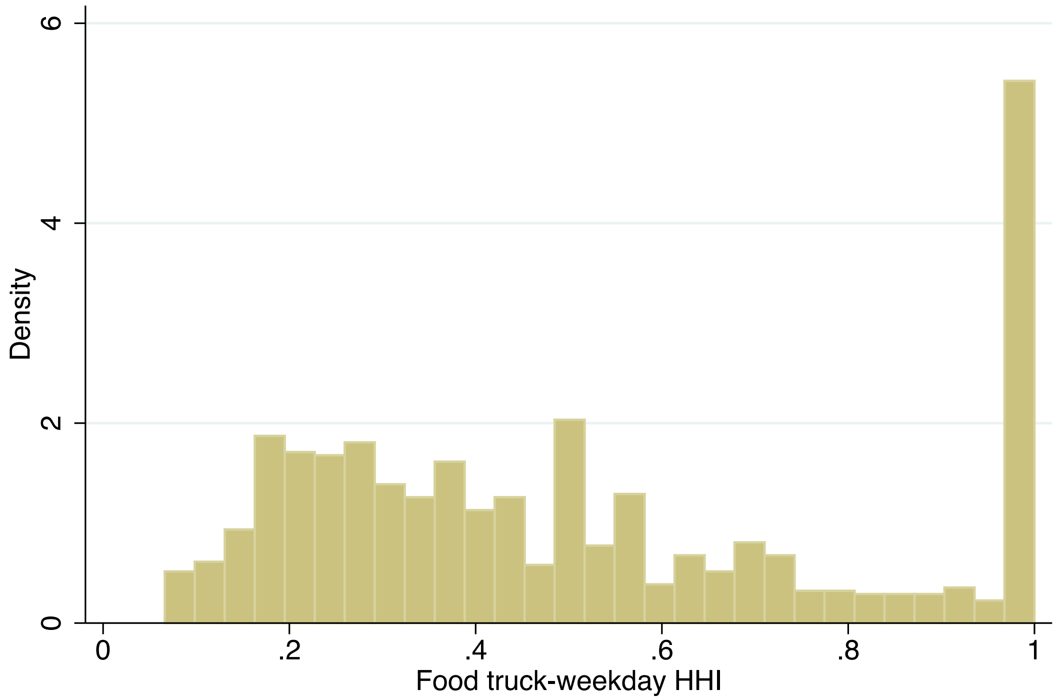


Note: This figure plots the distribution of $TruckHHI$ over trucks, where

$$TruckHHI_i = \sum_{j=1}^{J} \left(\frac{\#\text{ of days truck } i \text{ chooses location } j}{\#\text{ of days truck } i \text{ chooses to operate}} \right)^2$$

is the location concentration index for a single truck i. While a handful of trucks concentrate in a small number of locations, most trucks have a fairly diverse location portfolio. The average $TruckHHI$ across all trucks is 30%.

Figure 9: Distribution of Food Truck-Weekday HHI



Note: This figure plots the distribution of $TruckWeekdayHHI$ over truck-weekdays, where

$$TruckWeekdayHHI_{id} = \sum_{j=1}^{J} \left(\frac{\text{\# of days truck } i \text{ chooses location } j \text{ on weekday } d}{\text{\# of days truck } i \text{ chooses to operate on weekday } d} \right)^2$$

is the location concentration index for a single truck i on a given weekday d. There is a fairly strong tendency for trucks to follow fixed schedules, but there is still significant variation in where each food truck chooses to locate on a given weekday.

Table 1: Google Search Regression Results

Dependent Variable: Google Searches for Foodtruck	(1)	(2)	(3)	(4)	(5)
Google searches for S&S related terms	0.8331***	0.6816***	0.2952**	0.1919**	0.1875*
	(0.0265)	(0.0411)	(0.1061)	(0.0638)	(0.0829)
Searches for S&S * City population rank	-0.0150***	-0.0124***	-0.0144***	-0.0119***	-0.0120***
	(0.0008)	(0.0009)	(0.0021)	(0.0029)	(0.0022)
City FE	X	X	X	X	X
Year FE			X	X	X
Seasonal dummies	X	X	X	X	X
City-by-year demographic and economic controls		X			X
Only years where demographic and economic controls available		X		X	X
Observations	1908	1484	1908	1484	1484
R-squared	0.484	0.407	0.625	0.498	0.501

Standard errors in parenthesis

*** p<0.01, ** p<0.05, * p<0.1

Notes: Each observation is a city-quarter. Google searches is an index measuring the total number of google searches for a particular phrase in a city-quarter relative to the total number of google searches in that city-quarter. S&S related search terms include searches for "3g", "smartphone", "iphone", "android", "4g" and "twitter". Foodtruck searches include searches for "food truck". The sample period is 2004-2012. Demographic and economic controls include the average age of the population, percent white, percent male, average income, unemployment rate, percent with college degree, and population size. Specifications with year fixed effects have standard errors clustered at the year level.

Table 2: Google Search Regression Results, Granger Test

Dependent Variable: Google Searches for Foodtruck	(1)	(2)	(4)	(5)
Google searches for S&S related terms	0.2014***	0.1680***	0.1654	0.1468
	(0.0375)	(0.0385)	(0.0948)	(0.1128)
Google searches for S&S related terms* City population rank	-0.0052***	-0.0047***	-0.0053	-0.0048
	(0.0013)	(0.0012)	(0.0028)	(0.0031)
Google searches for S&S related terms 1 year ago	-0.3734***	-0.3414***	-0.3732*	-0.3469
	(0.0664)	(0.0669)	(0.1731)	(0.1699)
Google searches for S&S related terms 1 year ago* City population rank	0.0084***	0.0076***	0.0083	0.0077
	(0.0023)	(0.0023)	(0.0045)	(0.0044)
Google searches for S&S related terms 2 year ago	1.1239***	1.1541***	1.1118*	1.1251*
	(0.0631)	(0.0640)	(0.4630)	(0.4828)
Google searches for S&S related terms 2 year ago* City population rank	-0.0317***	-0.0310***	-0.0303*	-0.0300*
	(0.0024)	(0.0024)	(0.0122)	(0.0117)
Google searches for S&S related terms 1 year from now	-0.2024***	-0.2022***	-0.2200	-0.2212
	(0.0299)	(0.0302)	(0.1126)	(0.1041)
Google searches for S&S related terms 1 year from now* City population rank	0.0061***	0.0061***	0.0060	0.0059
	(0.0010)	(0.0010)	(0.0035)	(0.0033)
Google searches for S&S related terms 2 year from now	0.0041	0.0221	-0.0199	-0.0047
	(0.0232)	(0.0242)	(0.0354)	(0.0352)
Google searches for S&S related terms 2 year from now* City population rank	-0.0000	-0.0005	0.0000	-0.0005
	(0.0007)	(0.0007)	(0.0011)	(0.0013)
City FE	X	X	X	X
Year FE			X	X
Seasonal Dummies	X	X	X	X
City-by-Year Demographic and Economic Controls		X		X
Only Years where Demographic and Economic Controls are available		X	X	X
Observations	1060	1060	1060	1060
R-squared	0.449	0.467	0.453	0.471

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Each observation is a city, quarter. Google searches is an index measuring the total number of google searches for a particular phrase in a city/quarter relative to the total number of google searches in that city/quarter. For each city, the index value equals 100 in the quarter where the search item accounts for the highest share of searches. Smartphone searches include searches for "3g"+"smartphone"+"smart phone"+"iphone"+"android"+"4g". Foodtruck searches include searches for"food truck"+"foodtruck". Sample period is 2004 to 2012. Demographic and economic controls include the average age of the population, percent white, percent male, income, unemployment rate, percent with college degree, and population. Specifications with year fixed effects have standard errors clustered at the year level.

Table 3: Google Search Regression Results, Smartphone and Social Media Interaction

Dependent Variable: Google Searches for Foodtruck	(1)	(2)	(3)	(4)	(5)
Google searches for smartphone related terms 1 year ago	0.4045***	-0.1786*	0.0414	-0.2771	-0.3150
	(0.0959)	(0.1002)	(0.3022)	(0.1868)	(0.1964)
Google searches for social media related terms 1 year ago	0.0618	0.0365	0.0556	-0.0472	-0.0337
	(0.0428)	(0.0457)	(0.1208)	(0.1315)	(0.1289)
Searches for smartphone * Searches for social media, 1 year ago	0.0085***	0.0173***	0.0046	0.0163***	0.0166***
	(0.0014)	(0.0018)	(0.0052)	(0.0040)	(0.0037)
City FE	X	X	X	X	X
Year FE			X	X	X
Seasonal dummies	X	X	X	X	X
City-by-year demographic and economic controls		X			X
Only years where demographic and economic controls available		X		X	X
Observations	1696	1484	1696	1484	1484
R-squared	0.603	0.540	0.637	0.552	0.556

Standard errors in parenthesis

*** p<0.01, ** p<0.05, * p<0.1

Notes: Each observation is a city-quarter. Google searches is an index measuring the total number of google searches for a particular phrase in a city-quarter relative to the total number of google searches in that city-quarter. S&S related search terms include searches for "3g", "smartphone", "iphone", "android", "4g" and "twitter". Foodtruck searches include searches for "food truck". The sample period is 2004-2012. Demographic and economic controls include the average age of the population, percent white, percent male, average income, unemployment rate, percent with college degree, and population size. Specifications with year fixed effects have standard errors clustered at the year level. Each specification continues to include full interactions with city population rank.

Table 4: Twitter Data Summary Statistics

# trucks	200
# tweets	189,550
# location-related tweets	71,777
# uncertainty-related tweets	4,398
Avg. # tweets per truck-weekday	3.457
Avg. # location tweets per truck-weekday	1.386
Avg. # uncertainty tweets per truck-weekday	0.083
Share of truck-weekdays with ≥1 location tweets	0.687
Share of truck-weekdays with ≥1 uncertaint tweets	0.073

Notes: This table shows summary statistics for our Twitter data. Twitter feeds of 200 trucks from the DC metro area were collected from Sep. 2009 to Nov. 2013. The twitter data shows evidence that locational uncertainty is an important factor for food trucks, and that realization of these uncertainties is communicated in real-time on Twitter.

Table 5: Fraction of Google Search Results Returning Location Aggregators

MSA	**Top 10**	**Top 3**	**Top 1**
New York City	50%	67%	0%
Los Angeles	40%	100%	100%
Chicago	40%	100%	100%
Dallas-Fort Worth	20%	33%	0%
Houston	30%	33%	100%
Philadelphia	50%	33%	100%
Washington DC	40%	67%	100%
Miami	60%	100%	100%
Atlanta	10%	0%	0%
Boston	50%	67%	100%
San Francisco	60%	67%	100%

Note: "Top X" refers to the first X search results that Google returns in response to a search for "[City Name] Food Truck". Location-based websites include live maps, food truck finder apps, twitter aggregators, etc. Non location-based websites include food truck reviews, food truck associations, etc.

Table 6: Summary Statistics for Food Truck Location Data

Panel A: Basic food truck information (N = 204)				
	Min	Mean	Median	Max
Opening date	Jan 20, 2009	Feb 3, 2012	Apr 5, 2012	Mar 14, 2013
First observed operation date	May 2, 2012	Jul 12, 2012	May 16, 2012	Mar 14, 2013
Last observed operation date	May 3, 2012	Feb 19, 2013	Mar 28, 2013	Mar 29, 2013
Number days operated	1	80	67	207
Number locations visited	1	8.77	8	37
Twitter followers	0	2283.11	648.5	25591
FoodTruckHHI	0.045	0.303	0.212	1.000
Panel B: Dates information (N=217)				
	Min	Mean	Median	Max
Chance of rain	0	22.78	20	100
High temperature	0	68.60	73	102
Number trucks operating	4	75.30	78	110
Number trucks (Mondays)	4	59.35	62	84
Number trucks (Tuesdays)	38	74.40	77	97
Number trucks (Wednesdays)	30	80.47	83	110
Number trucks (Thursdays)	43	80.83	82.5	106
Number trucks (Fridays)	54	78.50	80	97
Panel C: Location information (N=70)				
	Min	Mean	Median	Max
Times visited (total)	1	233.42	23.5	2097
Avg. # trucks per day	0.0030	0.7031	0.0708	6.3160
Avg. # trucks per day (days with at least one truck)	1.0000	1.8800	1.0870	9.7083

Notes: This table shows summary statistics for our food truck location data. We observe the location decisions of each food truck each day from May 2, 2012 to March 29, 2013, except on weekends and except for a two week period between Dec. 22, 2012 and Jan. 1, 2013, for a total of 217 observed dates on which food trucks operated. FoodTruckHHI is the location concentration index within each food truck.

Table 7: Food Truck Location Choice Model Estimates

		Specification			
		(1)	(2)	(3)	(4)
Rain / Snow		-0.5384***	-0.3905***	-0.2676***	-0.2676***
		(0.0180)	(0.0087)	(0.0077)	(0.0077)
Cold (<50°F)		-0.2617***	-0.2705***	-0.1898***	-0.1898***
		(0.0111)	(0.0116)	(0.0095)	(0.0095)
Sales Tax		-0.5828***	-0.4418***	-0.3100***	-0.3100***
		(0.0127)	(0.0101)	(0.0083)	(0.0083)
Visited within last X days					
	1	-0.0874***	-0.0696***	-0.0543**	-0.3839***
		(0.0278)	(0.0278)	(0.0215)	(0.0166)
	2	-0.0411	-0.0488*	-0.0509**	-0.3297***
		(0.0298)	(0.0264)	(0.0222)	(0.0161)
	3	-0.0290	-0.0513*	-0.0585**	-0.2788***
		(0.0305)	(0.0271)	(0.0228)	(0.0174)
	4	-0.0169	-0.0548**	-0.0686***	-0.2203***
		(0.0276)	(0.0246)	(0.0209)	(0.0167)
	5	0.0092	-0.0500**	-0.0747***	-0.1517***
		(0.0266)	(0.0235)	(0.0199)	(0.0150)
	6	0.0150	-0.0724***	-0.1024***	-0.0769***
		(0.0207)	(0.0182)	(0.0154)	(0.0153)
	14	0.3158***	0.1237***	0.0200*	0.0255***
		(0.0149)	(0.0128)	(0.0107)	(0.0084)
	21	0.3968***	0.1467***	0.0056	0.0056
		(0.0142)	(0.0126)	(0.0105)	(0.0105)
Visited 7, 14, or 21 days ago		0.8114***	0.5490***	0.4272***	0.4272***
		(0.0112)	(0.0053)	(0.0044)	(0.0044)
Truck FE			X	X	X
Weekday FE			X	X	X
Location FE			X	X	X
Choice restriction				X	X
Log Likelihood		-53,939	-45,310	-41,293	-41,293
Observations		27,877	27,877	27,877	27,877

Note: Estimation results from location choice model described in section 5. Standard errors in parenthesis. *, **, *** indicate p-values of <0.1, <0.05, <0.01 respectively. "Choice restriction" indicates that each truck's choice set was restricted to locations that they were observed to have chosen at least once. Column 4 is identical to column 3 except that it reports cumulative effects.

Table 8: Food Truck Location Choice Model Estimates (Alternative specifications)

	Specification				
	(1)	(2)	(3)	(4)	(5)
Rain / Snow	-0.2676***	-0.2682***	-0.2639***	-0.2473***	-0.4019***
	(0.0077)	(0.0072)	(0.0109)	(0.0102)	(0.0088)
Cold (<50°F)	-0.1898***	-0.1911***	-0.1694***	-0.1750***	-0.2927***
	(0.0095)	(0.0096)	(0.0150)	(0.0135)	(0.0115)
Sales Tax	-0.3100***	-0.3113***	-0.2687***	-0.2454***	-0.4627***
	(0.0083)	(0.0084)	(0.0126)	(0.0119)	(0.0102)
Visited within last X days					
1	-0.0543**	-0.0523**	-0.0508	-0.0498	-0.0812***
	(0.0215)	(0.0218)	(0.0339)	(0.0316)	(0.0245)
2	-0.0509**	-0.0497**	-0.0532	-0.0545*	-0.0485*
	(0.0222)	(0.0223)	(0.0339)	(0.0323)	(0.0265)
3	-0.0585**	-0.0592***	-0.0613*	-0.0651**	-0.0479*
	(0.0228)	(0.0228)	(0.0341)	(0.0324)	(0.0285)
4	-0.0686***	-0.0686***	-0.0727**	-0.0774***	-0.0588**
	(0.0209)	(0.0210)	(0.0317)	(0.0291)	(0.0264)
5	-0.0747***	-0.0741***	-0.0806***	-0.0877***	-0.0565**
	(0.0199)	(0.0201)	(0.0306)	(0.0277)	(0.0273)
6	-0.1024***	-0.0993***	-0.1100***	-0.1210***	-0.0972***
	(0.0154)	(0.0155)	(0.0231)	(0.0212)	(0.0224)
14	0.0200*	0.0220**	0.0230	0.0001	-0.0069
	(0.0107)	(0.0108)	(0.0152)	(0.0137)	(0.0173)
21	0.0056	0.0075	0.0128	-0.0089	-0.0494***
	(0.0105)	(0.0106)	(0.0148)	(0.0134)	(0.0169)
Visited 7, 14, or 21 days ago	0.4272***	0.4176***	0.4352***	0.4302***	0.4273***
	(0.0044)	(0.0045)	(0.0066)	(0.0060)	(0.0062)
Truck FE	X	X	X	X	X
Weekday FE	X		X	X	X
Location FE	X		X	X	X
Choice restriction	X	X	X	X	X
Location X Weekday FE		X			
Experienced trucks			X		
Popular trucks				X	
Few location trucks					X
Log Likelihood	-41,293	-40,909	-22,244	-26,055	-14,192
Observations	27,877	27,877	13,774	15,805	13,321

Note: Estimation results from additional specifications reported in section 5.3. Standard errors in parenthesis. *, **, *** indicate p-values of <0.1, <0.05, <0.01 respectively. "Choice restriction" indicates that each truck's choice set was restricted to locations that they were observed to have chosen at least once. Column 1 is identical to column 3 of table 5 and is presented for the purpose of comparison.

Table 9: Food Truck Contribution to Restaurant Variety by Location

Location	# unique brick-and-mortar restaurants within 4 blocks	# unique brick-and-mortar restaurants within 1 mile	# unique food trucks per week	# unique food trucks per week (no mobility)
L'Enfant Plaza	26	153	39	26
Metrocenter	81	746	31	21
Farragut Square	117	1003	38	25
Union Station	23	610	31	20
Franklin Square	89	971	29	18
State Department	5	457	22	14
Navy Yard	1	99	18	12
West End	32	720	11	7
Tyson's Corner	23	218	8	8
Rockville	26	172	7	7
Average	42.3	514.9	23.4	15.8

Notes: Data for the number of brick-and-mortar restaurants at a location comes from Yelp searches for "restaurants" near the street address of the given location. Column 4 presents the number of trucks that would choose to locate at the given location in a counterfactual where location is fixed.

A Appendix (For online publication only)

A.1 Results on the steady state of the food truck location model

Here we derive the steady state of the food truck location model described in Section 2, both with and without mobile communication. We will also derive approximation results for the steady state expected quantity, and show that steady state expected quantity is always higher when mobile communication is available.

No mobile communication

For consumers in the announced location (call it j), the expected value to going out is:

$$V_{it} = (1-\lambda)\, u_{it} - K$$

For consumers in the unannounced location (call it k), the expected value to going out is:

$$V_{it} = \lambda\,(1-\lambda)\, u_{it} - K$$

Therefore, the mass of consumers going out at the announced location is:

$$\begin{aligned} Q_{jt} &= Q_{jt-1} F\left(u_0 - \frac{K}{1-\lambda} - \beta\right) + (1 - Q_{jt-1})\, F\left(u_0 - \frac{K}{1-\lambda}\right) \\ &= F\left(u_0 - \frac{K}{1-\lambda}\right) \\ &\equiv Q_A \end{aligned}$$

where the second equality follows from the fact that the announced location will always be one in which the food truck did not operate last period. The last equality is simply a definition for notational convenience.

At the unannounced location, the mass of consumers going out is:

$$
\begin{aligned}
Q_{kt} &= Q_{kt-1}\underbrace{F\left(u_0 - \frac{K}{\lambda\left(1-\lambda\right)} - \beta\right)}_{Q_{N\beta}} + \left(1 - Q_{kt-1}\right)\underbrace{F\left(u_0 - \frac{K}{\lambda\left(1-\lambda\right)}\right)}_{Q_N} \\
&= Q_{kt-1}Q_{N\beta} + \left(1 - Q_{kt-1}\right)Q_N \\
&= Q_N - Q_{kt-1}\underbrace{\left(Q_N - Q_{N\beta}\right)}_{\Delta} \\
&= Q_N - Q_{kt-1}\Delta
\end{aligned}
$$

Under this notation, Q_A is the quantity demanded at an announced location that was not visited last period, Q_N is the quantity demanded at an unannounced location that was not visited last period, and Δ is the penalty per unit sold in the same location last period.

In general, the ex-post demand for the truck in a period depends on three state variables:

$$s_t = \left(a_t, h_t, q_t\right)$$

so we can write:

$$Q_t = Q\left(a_t, h_t, q_t\right)$$

The state variables are defined as follows:

- The variable a_t defines the realization of the current period's locational uncertainty. a_t takes the value A if the announced location is accessible, N if the announced location is inaccessible but the non-announced location is, and O if neither location is accessible.

- The variable h_t defines, at the start of period t, the number of consecutive periods it has served the previous location, with $h_t = 0$ if the truck did not visit any place last period. h_t takes any value in the set of natural numbers.

- Finally, the variable q_t is the quantity that the truck sold at the start of its current streak of consecutive visits. So, for example, if $h_t = 3$ then $q_t = Q_{t-3}$. Note that q_t can only take the values of Q_A, Q_N, and 0. It takes the value of Q_A if the current streak of consecutive visits started at an announced location. It takes the value of Q_N if the current streak started at a non-announced location. Finally, it is defined to be 0 when $h_t = 0$; that is, when there is no current streak due to being out of the market last period.

We can fully specify demand as a function of state variables. If $a_t = O$ then the truck is out of the market and $Q_t = 0$. If $a_t = A$ then the truck can visit its preferred location, so $Q_t = Q_A$. If $a_t = N$ and $h_t = 0$, then this means the truck was out last period, but is unable to visit its announced location this period. Its demand is $Q_t = Q_N$. If $a_t = N$ and $h_t > 0$, then demand today is $Q_t = Q_N - Q_{t-1}\Delta$. So for $a_t = N$ and $h_t > 0$, we can solve for $Q\left(N, h_t, q_t\right)$ using the following recursion:

$$\begin{aligned} Q\left(N, 1, q\right) &= Q_N - q\Delta \\ Q\left(N, h, q\right) &= Q_N - Q\left(N, h-1, q\right) \text{ for } h > 1 \end{aligned}$$

The recursion yields the following expression for $Q\left(a, h, q\right)$:

$$Q\left(a, h, q\right) = \begin{cases} 0 & \text{if } a = O \\ Q_A & \text{if } a = A \\ Q_N & \text{if } a = N \text{ and } h = 0 \\ \frac{1-\left(-\Delta\right)^h}{1+\Delta} Q_N + q\left(-\Delta\right)^h & \text{if } a = N \text{ and } h > 0 \end{cases} \tag{4}$$

Now let $f\left(s_{t+1}|s_t\right)$ denote the transition probability for the state space. An unconditional distribution over the state space, $f\left(s\right)$, is a steady state if it satisfies the following:

$$f\left(s\right) = \sum_{s' \in S} f\left(s|s'\right) f\left(s'\right) \ \forall s \in S$$

Because a_{t+1} is independent of s_t, the transition matrix has the following form:

$$f\left(s|s'\right) = p\left(a\right) g\left(h, q|s'\right)$$

which implies that the steady state distribution must have similar form:

$$\begin{aligned} f(s) &= \sum_{s' \in S} p(a)\, g(h,q|s')\, f(s') \\ &= p(a) \underbrace{\sum_{s' \in S} g(h,q|s')\, f(s')}_{g(h,q)} \\ &= p(a)\, g(h,q) \end{aligned} \tag{5}$$

where

$$p(a) = \begin{cases} 1-\lambda & \text{if } a = A \\ \lambda(1-\lambda) & \text{if } a = N \\ \lambda^2 & \text{if } a = O \end{cases} \tag{6}$$

The deterministic transitions for h and q are given by:

$$(h_{t+1}, q_{t+1}) = \begin{cases} (0,0) & \text{if } a_t = O \\ (1, Q_A) & \text{if } a_t = A \\ (1, Q_N) & \text{if } a_t = N \text{ and } h_t = 0 \\ (h_t + 1, q_t) & \text{if } a_t = N \text{ and } h_t > 0 \end{cases}$$

We can therefore write the following:

$$g(0,0) = \sum_{h,q} f(O,h,q) = p(O) = \lambda^2$$

$$g(1,Q_A) = \sum_{h,q} f(A,h,q) = p(A) = 1-\lambda$$

$$g(1,Q_N) = f(N,0,0) = p(N)\, g(0,0) = \lambda^3 (1-\lambda)$$

And finally, for $h > 1$:

$$g(h,q) = f(N,h-1,q) = p(N)\, g(h-1,q) = \lambda(1-\lambda)\, g(h-1,q)$$

The above equation defines a recursion for $g(h,q)$. Solving the recursion, we obtain the following closed-form expression for $g(h,q)$:

$$g(h,q) = \begin{cases} \lambda^2 & \text{if } (h,q) = (0,0) \\ [\lambda(1-\lambda)]^{h-1}(1-\lambda) & \text{if } h>0 \text{ and } q = Q_A \\ [\lambda(1-\lambda)]^{h-1}\lambda^3(1-\lambda) & \text{if } h>0 \text{ and } q = Q_N \end{cases} \tag{7}$$

Equations (5)-(7) give us the closed-form solution for the steady state distribution $f(s)$. Combined with equation (4), we can write down the expression for the steady state expected value of Q:

$$\begin{aligned} E[Q] &= \sum_s Q(s) f(s) \\ &= p(A)Q_A + p(N)\begin{bmatrix} Q_N g(0,0) \\ +\sum_{h=1}^{\infty} Q(N,h,Q_A)\, g(h,Q_A) \\ +\sum_{h=1}^{\infty} Q(N,h,Q_N)\, g(h,Q_N) \end{bmatrix} \end{aligned} \tag{8}$$

The first order Taylor approximation around $\lambda = 0$ is:

$$E[Q] = (1-\lambda) F(u_0 - K) - \lambda K f(u_0 - K)$$

With Mobile Communication

With mobile communication, the steady state distribution of the state variables does not change because the accessibility to locations does not change, nor does the food truck's optimal strategy. What changes with mobile communication is that consumers can now make their decision on whether to go out based on the food truck's actual location, rather than its announced location. Therefore, at whichever location the food truck ultimately visits, the expected value for the consumer to going out becomes:

$$V_{it} = u_{it} - K$$

At the announced location, expected demand is:

$$\begin{aligned} Q_{jt} &= Q_{jt-1} F\left(u_0 - K - \beta\right) + \left(1 - Q_{jt-1}\right) F\left(u_0 - K\right) \\ &= F\left(u_0 - K\right) \\ &\equiv Q_A \end{aligned}$$

where the second equality follows from the definition of the announced location as one in which the food truck did not visit last period.

At the unannounced location, expected demand is:

$$\begin{aligned} Q_{kt} &= Q_{kt-1} \underbrace{F\left(u_0 - K - \beta\right)}_{Q_{N\beta}} + \left(1 - Q_{kt-1}\right) \underbrace{F\left(u_0 - K\right)}_{Q_N} \\ &= Q_{kt-1} Q_{N\beta} + \left(1 - Q_{kt-1}\right) Q_N \\ &= Q_N - Q_{kt-1} \underbrace{\left(Q_N - Q_{N\beta}\right)}_{\Delta} \\ &= Q_N - Q_{kt-1} \Delta \end{aligned}$$

As can easily be seen, the effect of mobile communication is to change the values of Q_A, Q_N, and $Q_{N\beta}$ in the steady state equation (8).

The first order Taylor approximation using the new definitions of $Q_A, Q_N, Q_{N\beta}$ gives us:

$$E\left[Q\right] = \left(1 - \lambda\right) F\left(u_0 - K\right) + \lambda \left[1 + F\left(u_0 - K - \beta\right) - F\left(u_0 - K\right)\right] F\left(u_0 - K\right)$$