UNIVERSITY OF CALIFORNIA,
IRVINE

Dynamic Network Models for the Analysis of Cooperation and Competition in New Markets

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTORATE OF PHILOSOPHY

in Management

by

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2015

DEDICATION

To my mother, Emily -

When I asked, you told me to look it up.

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ABSTRACT OF THE DISSERTATION

Dynamic Network Models for the Analysis of Cooperation and Competition in New Markets

By

Russel P. Nelson

Doctor of Philosophy in Management

University of California, Irvine, 2015

Professor Mary C. Gilly, Chair

This research consists of three essays which develop dynamic network models to examine the process of market creation. All three essays use Twitter data from gourmet food trucks operating in Southern California to explore how firms balance cooperation and competition. The first essay explores the role of status and proposes that market creation can be understood as the formation of a social hierarchy. The second essay examines the role of social contagion in influencing how mobile firms make location decisions. The third essay seeks to determine how cooperation emerges and is sustained within a group of competing firms despite rewards for selfish behavior. Taken together, these studies suggest that social processes drawn from research in sociology, anthropology, and evolutionary biology help firms to balance cooperation and competition during market creation. Further, this research provides a general framework for the exploration of dynamic networks in marketing.

<u>ESSAY 1:</u>

A Tweet, A Mention, A Market:

Towards A Status-based Model of Market Creation

Russel P. Nelson

The Paul Merage School of Business

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Introduction

Pursuing and maintaining social rank is an ongoing challenge for individuals in all human societies. It is also a key dilemma underscoring many core issues in marketing—how do brands gain influence? How do firms improve their position in a market? Firms, like individuals, are deeply concerned with their status (Podolny 2010). Yet the precise means through which firms gain social standing remains unclear. Research in marketing has tended to see markets as organized either by competition (e.g., competitive dynamics, marketing channels) or by cooperation (e.g., relational marketing, market creation). While it is clear that firms can gain advantage from both competition and cooperation, in many cases, it is important for managers to know how to balance these two strategies. When launching a business in a new market, when should they cooperate? When should they compete?

A third approach to the question of how firms gain prominence in a new market—the one taken in this research—is to theorize market creation as the establishment of a social hierarchy. As an alternative to power, firms in a new market can organize on the basis of status, commonly conceptualized as an individual's prestige or social honor as judged by their peers (Weber 2009). Social hierarchies, defined as the "rank order of individuals or groups on a valued social dimension" (Magee and Galinsky 2008, p. 354) are universal systems for organizing in social groups (Mazur 1985). When cooperative living brings increased competition for limited resources, a social hierarchy often emerges, serving as a governance structure to reduce the tension between cooperation and competition and limit conflict. Individuals with more status are ranked higher in the social hierarchy and receive priority of access to resources. Individual with less status are ranked lower in the social hierarchy and must defer to higher ranking group members. In a market, status affects the opportunities available to a firm in comparison to those available to its competitors (Podolny 1993). Three issues are relevant in considering market creation as the organization of a social hierarchy.

The first issue centers on the relevance of status to performance in a new market. Previous research has found status effects in established markets with strong traditions such as the wine industry (Benjamin and Podolny 1999), "white shoe" law firms (Rivera 2012), and the *guanxi* networks in China's consumer products industry (Gu et al. 2008). New markets, however, lack the deep-rooted social hierarchies found in established markets. Much research in marketing has noted the role of pioneer advantage in explaining performance in new markets (e.g., Carpenter and Nakamoto 1989). These findings suggest that a firm's status might be much less salient than the timing of a firm's market entry in driving performance. The literature on pioneer advantage may lead to the question, Does status matter to firm performance in a new market?

If status is important to firm performance, then the second issue is how do firms in a new market acquire it? At their most basic, hierarchies emerge from independent dyadic interactions, where individuals use only their own personal attributes to establish rank over another (Chase 1980). Just as a chicken earns its place in the pecking order by winning pecking contests (Schjelderup-Ebbe 1935), individual firms learn their rank through dyadic exchanges with other firms. While in many animal groups, individuals can gain status solely through physical competition, in human groups, competition alone is not enough. Weaker individuals can form coalitions, preventing a stronger individual from gaining rank (Mazur 1985).

Therefore, the third issue is the role of status at the market or network level. While dyadic interactions shape how firms gain or lose status, the market as a whole is interdependent, as the status of every firm in a market is interrelated to the status of other firms. Firms form coalitions and alliances and evaluate potential partners based on the status of their current partners (Baum and Oliver 1991). While high ranking firms are motivated to sustain the hierarchy, low ranking firms stand to benefit by disrupting it. Moreover, new markets are characterized by the entry and exit of firms and rapidly changing patterns of interaction. What social mechanisms emerge to balance cooperation and competition and sustain the social hierarchy as the cast of actors changes over time?

This study draws on social hierarchy (Mazur 1973, Chase 1980) and status (Podolny 1993) theory from sociology to illustrate the benefits of status to individual firms and to postulate that status operates as a governance mechanism that helps firms to balance cooperation and competition and shapes the market creation process. Previous work in marketing has identified the importance of social capital—"the sum of the resources, actual or virtual, that accrue to an individual or group by virtue of possessing a *durable* network of more or less institutionalized relationships of *mutual* acquaintance and recognition" (Bourdieu and Wacquant 1992, p. 14; italics added)—in marketing alliances (Swaminathan and Moorman 2009), relationships between suppliers and customers (Tuli et al. 2007), Chinese *guanxi* networks (Gu, Hung, and Tse 2008; Sheng et al. 2011), and enhancing firm performance (Xiong and Bharadwaj 2011).

This article suggests that social capital is part of the broader phenomenon of status and extends previous research by showing that interfirm relationships can be beneficial even when they are neither durable nor mutual. I propose that social hierarchies are a more generalized structure than previously shown in the literature and can be emergent, arising in new markets where individual entrepreneurs lack the centuries of tradition that produce *guanxi*. In short, my study addresses the following questions: (1) Is a market a social hierarchy? (2) Does rank in the social hierarchy matter to firm performance in a new market? (3) How do firms in a new market acquire status? and (4) What social mechanisms emerge to sustain the social hierarchy over time? Exploring the links between status and competition is not only a theoretical exercise—managerially, it suggests new strategies for how firms can best gain status to enhance their competitive edge.

I test my hypotheses using multiple novel network methods to model the emergence of the Southern California gourmet food truck market. Traditionally, food trucks sold inexpensive fast food outside construction sites and bars. In November 2008, chef Roy Choi co-founded Kogi BBQ, a truck that sold gourmet tacos and used Twitter to announce its location to its customers. In May 2009, food trucks began using Twitter to interact not only with customers, but also with each other, messaging, responding to, and commenting on other trucks' tweets by mentioning their Twitter usernames.

Several features makes this setting attractive for studying the emergence of social structure in a new market. It was important to select an industry in which interfirm interactions were frequent, changed noticeably over time, and were readily observable. The case also needed to be one in which a social hierarchy was created by a network of social actors working to define a new market space. Although food trucks have existed in Los Angeles since at least the 1960s, the influx of new entrepreneurs and the separation between gourmet food trucks and traditional food trucks (which don't use Twitter) meant that the social hierarchy would be emergent and not a continuation of an existing social structure. In contrast with relational marketing research, which has focused on formal, mutual ties, it was important for the interactions between firms to be informal and directed. As I propose that a social hierarchy functions as a governance structure, it was important to study a market with little formal governance and market interactions that lacked the legal oversight present in strategic alliances or co-marketing agreements. Mentions on Twitter met this criteria.

Conceptual Framework

Status, Defined

Status is defined as the prestige, respect, and esteem that an individual receives from others (Fiske 2010). As status originates externally, from the evaluations of others, one can only have status if others confer it (Blau 1964). Status and power and related but distinct concepts. Power is conceptualized as an individual's control over resources (Magee and Galinsky 2008). Compared with status, power is less reliant on the judgments of others (Blader and Chen 2012) and is more a property of the individual themselves (Magee and Galinsky 2008).

While power can be a source of status and status can be a source of power, they are not necessarily synonymous. Some individuals have both power and status, others neither power nor status, and it is possible to have one without the other. In some markets, the highest status player also has the largest market share, as in Google's domination of internet search. In other markets, the highest status firm is a small, niche player. Consider luxury handbags, for instance: Coach has the largest market share but is not the highest status player. Similarly, McDonald's has a larger market share than In N Out, but lower status. Hierarchies are fundamental frameworks organizing social life (Weber 2009). Marketing has largely looked at order in a market as arising from power, as in a firm's ability to coerce or outcompete its rivals. The difference provided by status, as opposed to power, is that one gains status through both cooperative and competitive strategies, rather than competition alone.

The Function of Status in New Markets

The threat of opportunism is a key issue when building a relationship with another firm. To promote cooperation, research in the relational marketing paradigm suggests that firms aim for fair and even exchange relationships. To this end, firms can avoid power imbalances (Bucklin and Sengupta 1993) and use formal contracts and the threat of legal retribution to protect themselves (Williamson 1975). By focusing on contractual relationships, such as strategic alliances and co-branding agreements, relational exchange research has overlooked firms' informal and asymmetric relationships. Innovation can outpace regulation during the market creation process, so firms in new markets often interact without legal safeguards. For instance, competitors form relationships by virtue of their physical proximity or shared resources. Uber and Lyft do not have a strategic alliance, but they share many of the same drivers.

The relational marketing perspective aims to promote cooperation by limiting asymmetry in individual exchange relationships. Here, we suggest instead that the network of asymmetrical relationships form the foundation of a cooperative social structure. Status operates through an asymmetric relationship, deference: a lower status individual will treat a higher status individual with greater consideration and courtesy than he or she expects to be treated in return (Harsanyi 1976). Rather than aiming for balanced exchange relationships, the perspective afforded by status assumes that there are differences between firms. These differences place firms in a social hierarchy with unique social norms, operating mechanisms, and influences on firm behavior. Status determines which individuals receive access to scarce resources, limiting conflict between group members. Individuals cannot act purely out of self-interest. What leads individuals to cooperate is not formal contracts but the prospect of losing their reputation as reliable partners (Baumard et al. 2013). Thus instead of viewing asymmetry as something to be regulated, we see asymmetry itself as a means of regulation. A social hierarchy, made up of a network of asymmetrical relationships, promotes cooperation and can serve as a governance structure during the market creation process.

By impacting the allocation of resources among individual firms, over time, status shapes the pattern and rate of market growth (Podolny 1994). New markets feature a high degree of uncertainty. When the quality or value of goods to be exchanged is difficult to discern, market actors shift their focus from what is offered to who is making the offer. In an uncertain context, the status of potential exchange partners is observable via their previous pattern of exchange relations. Higher status firms thus become more attractive exchange partners and begin to accumulate advantage over lower status firms. For example, the smartwatch is a new product category featuring a high degree of uncertainty. Apple's high status position in the smartwatch market derives in large measure from its status in the related smartphone and personal computer markets.

Status in the Gourmet Food Truck Market

As one of the goals of this research is to understand how firms gain status, it is important to note what status or influence means on Twitter. As a social network, Twitter was launched with the instruction for users to "tell the world what you're doing" but quickly became a platform grounded more in interpersonal communication. On Twitter, users have three primary ways of interacting with other users: they can *follow* updates of other users who post content they find interesting; they can then repost this content to their own followers by *retweeting* the message; and they can respond to and comment on other users' tweets by *mentioning* their @username (Cha et al. 2010). The number of followers represents the size of the audience for that user while the number of mentions indicates the ability of that users to engage others.

Within the food truck industry, firms initially used Twitter as a one-way communication tool to announce their location to their customers. As customers began to mention the trucks on Twitter—for example, requesting that a truck visit their neighborhood—it became a two-way medium for trucks to increase customer engagement. Six months into the market, owners began using Twitter mentions to communicate amongst themselves.

As status is defined in terms of perceptions, a key issue is understanding what factors firms use to judge each other's status. Previous research on status among Fortune 500 corporations has linked profits, assets, charitable donations, and market share to a company's status (Fombrun and Shanley 1990). In the food industry, status is associated with a number of factors, including creativity, quality, training, reviews, awards, and popularity (Benjamin and Podolny 1999; Rao et al. 2005). In judging status, individuals often rely on the most easily observed factors, such as a job candidate's educational affiliations or a bank's trading partners (Podolny 1994). Factors such as profits, creativity, and quality are more difficult to observe in the gourmet food truck market, but a truck's follower count on Twitter is easily observed and continuously updated. As a means of "keeping score," the follower count is commonly used by users to compare themselves to their friends and colleagues (Leonhardt 2011). Following Toubia and Stephen's (2013) study of Twitter user motivations, I use the number of Twitter followers as a measure of the stature or prestige of a Twitter user.

Social rank is defined as one's position in a social hierarchy and reflects the relative deference an individual receives from their peers. On Twitter, a mention from one user to another is a form of deference. In their study of celebrities on Twitter, Marwick and boyd (2011) find that the use of Twitter mentions reflects power differentials. Fans mention famous people to display a relationship or affiliation. A fan sending a mention to a celebrity is a gesture that resembles gift-giving, with the fan hoping for public acknowledgement of their gift. If a celebrity mentions back, the fan considers it a badge of status. Following Marwick and boyd, I consider a Twitter mention from one truck to another to be a form of deference. A mention can benefit the recipient as the recipient's @username is promoted to the sender's Twitter followers, some of whom may decide to follow the recipient's account or eat at their truck. The sender of the mention bears the burden.

It follows then that I determine the social rank of a truck not by its number of Twitter followers—a measure of its influence among customers—but by the mentions it receives from other trucks—a measure of its influence among its peers. If status were only determined by the value of an individual's previous efforts in a market, than it would differ little from the number of Twitter followers. What makes an individual's status a distinct construct is that it derives not only from the value of the individual's previous efforts, but also from the status of those with whom the individual engages in exchange relations (Podolny and Phillips 1996). What is important is not only the amount of deference shown to each individual, but also the relative standing of the individual making the gesture. Because they are judged by the company they keep, firms need to choose whom they defer to carefully. Deferring to too many low-status firms can hurt high-status firms, just as receiving deference from high-status firms can help firms of low status.

Hypotheses

Does Status Matter? Direct Effects of Status on Performance in a New Market

Following Klepper and Sleeper's (2005) study of market evolution, I measure performance in terms of spinoffs. I have opted to analyze the likelihood of a food truck launching a brick and mortar restaurant for two reasons. First, I can observe this metric for all firms in the sample. Accounting-based metrics, such as sales or market share, are not available for private companies such as food trucks. Alternative measures of organizational performance, such as survival, are noisier in this seasonal industry because as the market contracted in 2012 and 2013, some owners began going on hiatus in the winter. Thus it is not always evident whether a firm is on temporary hiatus or out of business. The second reason why I model spinoffs is that it represents an extremely important milestone in the restaurant industry and for food trucks in particular. Starting a food truck is a cheap way to enter the restaurant industry and test a product concept (Berl 2012). However, food trucks have difficult working conditions, with many long hours spent in a confined space. Food trucks also have limited profits, as they are capacity constrained and cannot sell alcohol, a high margin product that keeps many restaurants in business. As a result, many owners aspire to use their truck as a stepping stone towards opening a brick-and-mortar restaurant.

Status is a cue or proxy used to judge an organization's quality and abilities (Merton 1968). Previous research suggests that high status leads to perceptions that a firm performs at a high level and leads their industry. High status organizations are attractive alliance partners and are sought out for partnerships (Shipilov 2005). Higher status organizations are considered less risky by lenders and are able to acquire resources, such as loans, at a lower cost (Podolny 1993). Given the effort that food truck owners exert in cultivating their status and the salient role of status in enhancing access to resources essential to business operations, I hypothesize the following:

H1: A firm's rank in a social hierarchy has a positive effect on its market performance – as measured by the likelihood of it spinning off a brick and mortar restaurant.

How Firms In A New Market Acquire Status

As trucks gain status in the market when other trucks show them deference, in the form of Twitter mentions, a key challenge is then how to acquire deference. In other words, what guides firms as they choose whom to show deference? Deference is freely conferred—trucks cannot use force or the threat of force to gain deference from others. Trucks can also not elicit it—to have to ask for deference would lower one's status (Goffman 1956). Rather, status rests on merit in the eyes of others.

The number of Twitter followers is a measure of a truck's influence with customers and a proxy for a truck's quality and success in the market. Trucks with more Twitter followers often have spent more time in the market and thus have accumulated greater knowledge of effective strategies and more financial success. Deferring towards a truck with more Twitter followers shows regard for their accomplishments. Ties with more prominent firms can also have a reputational or signaling effect that helps a young firm to overcome the liability of newness (Gulati and Higgins 2003). It is also an advertising association (Pechmann and Ratneshwar 1991) that allows the sender's Twitter followers to associate a newer truck with the attributes of a more established one. As firms are judged by the quality they keep, firms who are trying to gain status should attempt to associate with firms that already have it. High status firms risk losing their status if they associate with lower status firms, as observers then question whether the high status party is worthy of the respect conferred to them (Podolny 2010). This suggests:

> H2: Firms with fewer Twitter followers are more likely to mention firms with more Twitter followers.

In addition to its ceremonial aspects—the salutations, compliments, and apologies through which the sender depicts their appreciation of the receiver—deference can also take the form of avoidance rituals and taboos, which imply acts the sender should refrain from doing (Goffman 1956). While a mention is a public sign of respect and recognition shown to another, it is also a promotion that advertises the mentioned user to the sender's followers. Although direct competitors may have mutual admiration or respect for each other, one would expect them not to promote their competitors. The cost of publically declaring respect and promoting a rival to one's followers would seem to outweigh any benefits. As one would expect that firms would keep rivals at a distance, I predict the following:

> H3: Firms are less likely to mention direct competitors.

Deference reflects the sender's desire to be in proximity to the receiver. Animals in many group-living species can identify group members who are more successful foragers (Giraldeau and Lefebvre 1986). For less successful foragers, a useful strategy is "scrounging," where they identify successful food producers and maintain proximity to them in order to feed from their food finds. Consider the classic African image of hyenas waiting for lions to finish feeding on a kill so they can move in and scavenge the leftovers. Showing deference to a more successful forager makes it more likely that they will tolerate scrounging.

Firms in a new market can be considered foragers. The creation of new markets is fraught with incomplete information, so firms engage in a search and selection process (Sarasvathy and Dew 2005). Consumer preferences and demand are uncertain, so firms explore different strategies and then exploit those which seem most promising. In the early stage of the gourmet food truck market, trucks lack knowledge of the most fruitful locations. However, some trucks, such as Kogi, are more successful foragers, in that they are able to attract more customers when they park at a new location. Other trucks are less successful foragers and can use a scrounging strategy, where they attract customers by maintaining proximity to more successful foragers. This can take the form of co-locating, an agglomeration behavior where a less successful truck parks with a more successful truck. Or it can take the form of social-learning, where a less successful truck observes where the more successful is parking and later visits those areas.

I consider the extent to which two trucks' vending territories overlap to be a measure of territory competition. When there is competition for territory, there are two ways to reduce conflict: either the territory should be strictly divided between competitors, as when solitary predators, such as tigers maintain their own ranges, or the weaker individual should show deference to the stronger individual, as when hyenas wait for lions to feed. When trucks have no overlap in vending territory, there should be little opportunity or incentive for them to interact and one would expect to see little deference exchanged. In contrast, as the overlap in vending territory increases, so too does the competition for customers in that territory. To reduce the tension and avoid conflict, trucks should be more likely to show deference. Thus we would expect:

H4: The level of territory competition between two firms has a positive effect on the likelihood of a mention.

In order to form and maintain relations with others, individuals must generally be in physical proximity (Butts and Carley 2002). This is true even for digital communication, such as email (Carley and Wendt 1991). Food trucks are required to park at night at commissaries, which are shared garages with facilities for cleaning, food preparation, and food storage. Southern California has several dozen commissaries. Owners choose which commissary to park at on the basis of service, cost, and location convenience. Owners also consider the type of trucks who use the commissary, as some cater to traditional taco trucks while others are used by gourmet food trucks. Sharing a commissary with another truck increases physical proximity and provides greater opportunity for face-to-face interactions. Previous research suggests that digital communication is more likely when individuals have opportunities for face-to-face interactions (Kossinets and Watts 2006). Given that sharing a commissary presents opportunities for face-to-face interaction and that face-to-face interaction increases the likelihood of digital interaction, I expect:

H5: Sharing a commissary increases the likelihood of a mention.

How Firms In A New Market Acquire Status: The Role of Reciprocity

A particular act of deference is something a sender gives to a receiver. But it is also an exchange that can create an obligation for the receiver to reciprocate (Sahlins 1972). An individual may be unlikely to reciprocate in a one-off exchange, however, repeated interactions introduce concerns including the need to maintain and stabilize relationships as well as the ability and willingness of the other party to fulfill their side of the bargain (Rousseau and Parks 1993). Individuals monitor exchange relationships to determine whether to continue the exchange and have a preference for reciprocated relationships. Over time, reciprocated exchanges create relationships involving trust, predictability, and ongoing interactions. Given the preference for reciprocity in exchange relationships, I predict:

H6: The likelihood that a mention is reciprocated increases over time.

Whether an individual reciprocates an act of deference depends in part on the relative status of the two parties involved in the exchange. Research suggests that higher status individuals have a greater tendency to act more self-interested (Piff et al. 2012). Abundant resources and elevated rank provide higher status individuals with greater freedom and independence (Kraus et al. 2009), creating self-focused patterns of behavior (Kraus et al. 2011). While individuals generally adhere to group norms for fear of disapproval or reprimand, high status individuals are in a powerful position that allows them to risk the social costs of not conforming without fear of losing their place in the social hierarchy (Bellezza et al. 2014). Between status equals, one would expect to find symmetry in the exchange. Between a superordinate and a subordinate one may expect to find asymmetrical relations, the superordinate having a greater tendency to reject the obligation to reciprocate and the subordinate having a greater tendency to conform to the obligation to reciprocate. Thus previous research on status and social norms suggests:

> H7: Firms with fewer Twitter followers are more likely to reciprocate mentions from firms with more Twitter followers.

Market Creation As Social Hierarchy: The Emergence of Social Processes

Once a hierarchy is established, a number of social processes emerge to maintain status for individuals at different levels of the hierarchy (Magee and Galinsky 2008). These processes affect all members of the hierarchy so as to perpetuate the established order. Although low ranking members are disadvantaged relative to high ranking members, the hierarchy provides benefits that motivate even low ranking members to invest in its continuation. As a hierarchy limits conflict between group members and satisfies individual needs for order and stability (Jost and Banaji 1994), most group members are motivated to reinforce it, rather than disrupt it. I consider five social processes that help reinforce hierarchical arrangements: reciprocity, persistence, recency, triadic closure, and preferential attachment. Each of these processes helps to support hierarchical differentiation and makes it difficult for individuals to challenge the status quo once the hierarchy has been established.

Tweets are public and firms have the opportunity to observe where their competitors are directing their attention. So one would expect that firms would notice which other firms are receiving a larger share of attention. As individuals have a preference for associating with higher status individuals (Gould 2002), it follows that they would have a tendency to direct their attention towards those higher status individuals as well. As the network develops over time, one would then expect to observe an accumulative advantage (Merton 1968) phenomenon, in which firms which experience early success capture a larger share of subsequent rewards. Thus:

H8: The social hierarchy is sustained by a tendency for preferential attachment.

Reciprocity is one of the first social processes that emerges to stabilize exchange relationships. Given the temptation to cheat in an exchange, the “tit for tat” of reciprocity is a way to monitor a trading partner (Axelrod 1981). Within a hierarchy, it serves as a constraint that maintains an individual’s status level and prevents them from increasing their status. People prefer to associate with high status individuals, but they also want their attention to be reciprocated (Gould 2002). However, high status individuals do not have enough attention to give to the many low status individuals who desire their company. They also do not benefit by reciprocating attention from lower status others. When low status individuals fail to receive reciprocation from high status individuals, they will focus their attention on status equals, who are more likely to reciprocate. As a result, the preference for reciprocity helps to separate low status and high status individuals, maintaining the status order. Thus:

H9: The social hierarchy is sustained by reciprocity.

In addition to reciprocity, there are other social processes that emerge to maintain the social hierarchy. Repeat partnering between firms increases trust (Wuyts et al. 2004). If a firm has two exchange partners, the firm should have a preference for the partner who has a longer history of exchanging with them. Similarly, if a firm has two exchange partners, the firm should have a preference for the partner with which it has most recently exchanged. Thus:

H10: The social hierarchy is sustained by a tendency for persistence.

H11: The social hierarchy is sustained by a tendency for recency.

An additional structural feature of networks and social hierarchies is transitivity. Consider three individuals, *A*, *X*, and *B*. If *A* shows deference to *X* and *X* shows deference to *B*, then what to make of the relationship between *A* and *B*? In a hierarchy, transitivity means that not all individuals need to interact to determine the rank order. If an individual enters a social group and loses a contest to a competitor ranked second, they do not need to engage the first-ranked competitor. So as the strength of the *A*-*X* and *X*-*B* ties increase, so too does the likelihood of an *A*-*B* tie. If *A* defers to *B*, then this is an example of triadic closure. This is true among firms as well, as research suggests that firms are more likely to interact when they share a common partner (Uzzi 1997). Thus:

H12: The social hierarchy is sustained by a tendency for triadic closure.

Data and Methods

Data

In line with previous studies of interfirm collaboration (Ho and Ganesan 2013; Rindfleisch and Moorman 2001), I used three industry directories—RoamingHunger.com, FoodTruckMaps.com, and FindLAFoodTrucks.com—to create a list of 554 food trucks operating in Southern California. A data reseller then used the Twitter Firehose API to obtain a list of all tweets sent by those accounts over a four-year period, beginning with Kogi BBQ's first tweet on November 21, 2008. In total, 700,121 Tweets were collected. Figure 1 shows the increase in the number of food trucks and Tweets over time. The food truck market features the common S-curve pattern from diffusion research (Mahajan et al. 1995): the number of trucks and Tweets increases slowly, then accelerates before slowing and leveling off.

While the first food truck Tweet was on November 21, 2008, food trucks did not begin mentioning each other on Twitter until May 5, 2009. In this work, as the focal phenomenon is the emergence of market structure, I focus on the mentions exchanged between trucks over a one year observation period between May 5, 2009 and May 4, 2010. I select all Tweets sent by the accounts of the 85 trucks present in the market during that year as well as the Tweets sent between Kogi's entry and the start of the observation period. In total there are 59,511 Tweets in my dataset. Of the 56,273 messages sent over the one year observation period by the focal firms, 1,472 (2.6%) mentioned at least one other food truck. Each Tweet is coded according to the Twitter User ID of the sender and recipient, creating a dyadic data set of directed ties. Where one-to-many communications were found, such as a user mentioning multiple Twitter accounts in one message, I coded each as a series of dyadic communications from the sender to each of the named recipients (in the order named). For instance, @buttermilktruck: "RT @eattoblog: just nominated @ButtermilkTruck @thegastrobus @donchowtacos for the LA Vendy Awards!

http://su.pr/18AFXW" is coded as a tie from the Buttermilk Truck to the Gastro Bus, then a tie from the Buttermilk Truck to Don Chow Tacos.

In essence, the emergence of the gourmet food truck market is represented as an ordered sequence of 2,294 dyadic messages, each having a sender and receiver. Coding the data in this way has several benefits. First, it allows recreation of each interaction at the mention level, that is, who Tweets whom and at what time in the formation of the market. Second, and perhaps more importantly, it allows for aggregation of individual mentions to the alliance level. I can trace the number of mentions exchanged between firms, the timing of the mentions, the extent to which they were reciprocated, as well as the length of such exchanges.

An important restriction in the market is that trucks are required to park nightly at commissaries, which are garages with shared food preparation and storage facilities. Data on which truck parked at which commissary was obtained from a combination of business license records, public health permits, and food facility inspection records as well as pictures of the food trucks, which often have the commissary address stenciled on the side (Figure 2). This is important as not only does the location of the commissary influence the choice of vending locations by impacting the travel distance required, but owners and workers also interact informally at the commissaries. For example, @barbiesq: "@kogibbq Hey, its John frm BBQ truck. At the yard. Your cold truck is SERIOUSLY leaking oil from refir. You may lose your refrigeration!" Thus informal interaction at the commissary becomes another way for owners to share knowledge and advice and build familiarity and trust, leading to greater likelihood of mentioning each other on Twitter.

The second set of data is extracted from the content of the Tweets themselves. Trucks use Twitter to announce their vending locations, although the formatting of these messages is as idiosyncratic as the individual users. Using natural language processing, I extract the locations and then geocoded the addresses using the Bing Maps API. In total, of the 59,511 Tweets sent between November 21, 2008 and May 5, 2010, 41,054 (69.0%) announce a location. There are 2,496 unique geolocations (See Figure 2). As I describe in the next section, I use these data to ascertain the extent to which the territory of any two trucks in the market overlap—that is, geographic points that might serve as contested ground for dominance disputes or market competition more generally.

Decoding the meaning of cooperative networks and interactions themselves is difficult without a qualitative understanding of the gourmet food truck market, its key actors, and the subjective meaning they give to it. To guide the network analysis and serve as a member check on the findings, I also draw from secondary sources, including news stories and posts by food bloggers as well as five years of observations at food truck events and interviews with 12 food truck owners and the director of an industry lobbying organization, the Southern California Mobile Food Vendors Association. This research was designed to gather data on how food truck owners understood their interactions on Twitter, what their subjective reasons are for cooperating with other owners and mentioning them on Twitter, and how social norms link seemingly disparate online interactions.

Methods

Following procedures from previous studies of status and dynamic communication in sociology, I analyze the establishment of the social hierarchy in the gourmet food truck market using three approaches—an Elo-rating procedure (Elo 1978; Neumann et al. 2011), a dyadic-level analysis (Papachristos 2009), and a relational event model (Butts 2008). The goal of the first analysis, Elo-rating, is to determine the hierarchical pattern of interfirm communication, describe its basic properties, and assess its stability. The second and third analyses explore possible mechanisms responsible for the creation of the communication network, the establishment of the subsequent hierarchy, and its stability over time.

Elo-rating model

Elo-rating is a method used for calculating the relative skill levels of players in competitor-versus-competitor games including chess, American college football, and Major League Baseball (Elo 1978). It has been extended to status contests in animal hierarchies (Albers and de Vries 2001). The essential idea is that each player's underlying skill becomes evident through competition with the other players. At the beginning of the rating process, each individual starts with a predefined rating, for example, a value of 1000. A player's Elo rating increases or decreases from the initial value of 1000 based upon the outcome of each game, with the winner taking points from the loser. The number of points gained or lost depends on the expectation of the outcome, i.e., the probability that the higher-rated individual wins. Expected outcomes (a high-rated player beating a low-rated player) lead to smaller changes in ratings than unexpected outcomes (a low-rated player upsetting a high-rated player). This means that the rating system is self-correcting: a player whose rating is too low should over the long run, do better than the system predicts, thus gaining points until their rating reflects their underlying skill. Depending on whether the higher-rated individual wins or loses an interaction, ratings are updated according to the following formulae:

Higher-rated player wins: (1)

$$\text{WinnerRating}_{\text{NEW}} = \text{WinnerRating}_{\text{OLD}} + (1\text{-}p) \text{ x } k$$

$$\text{LoserRating}_{\text{NEW}} = \text{LoserRating}_{\text{OLD}} - (1\text{-}p) \text{ x } k$$

Lower-rated player wins (beating expectations):

$$\text{WinnerRating}_{\text{NEW}} = \text{WinnerRating}_{\text{OLD}} + p \text{ x } k$$

$$\text{LoserRating}_{\text{NEW}} = \text{LoserRating}_{\text{OLD}} - p \text{ x } k$$

where p is the expectation of winning for the higher-rated individual, which is a function of the absolute difference in the ratings of the two players before the contest, and k is a constant that determines the number of ratings points that an individual can gain or lose after a single contest.

Market creation is a process that establishes order. Much research in marketing has drawn from economics, viewing order—generally conceptualized as market equilibrium—as a consequence of voluntary action by rational, self-interested individuals. To this end, research has modeled competitive dynamics within a market as a game or series of contests between multiple players, where the outcome for each player depends on the collective actions of all players involved. In game theoretic models, winning or losing is generally evaluated in terms of each player's market share. Order is derived from the aggregate strategies of the individual players. For example, the equilibrium in the cola market is a function of the advertising and pricing strategies used by Pepsi and Coca-Cola (Gasmi et al. 1992). The game theoretic perspective has provided much insight into the workings of markets, however, it is less useful for heterogeneous, complex situations, such as social interaction between a large number of individuals because reduction becomes more difficult.

As in game theoretic models, I view market creation as a series of contests that establishes order. Because food trucks are private businesses, I lack data on sales and market share. However, I do have data on social interactions. Given the data, I thus utilize a sociological approach, conceptualizing order as a social hierarchy, an ordered social structure whose continued reproduction relies on normative consensus. In my analysis, winning or losing is evaluated not in terms of market share but in terms of status. This offers an alternative perspective to the question of how markets self-organize, one that provides a richer account for such factors as the influence of institutions, relationships, and location in social networks.

As Elo-rating is based on a sequence of contests, it is fitting for studying a dynamic process such as market creation. To estimate the Elo-rating model, I use the sequence of mentions exchanged between the trucks over the one-year observation period. I consider each mention as an act of deference from the sender to the receiver. Each truck enters the market with an initial status rating of 1000. As an act of deference, sending a mention to another truck lowers the status of the sender and raises the status of the receiver. At the end of the mention sequence, the truck that has received the most deference receives the highest rating and is ranked first in the status order, the truck with the second-highest rating is second, et cetera.

Elo-rating has several advantages as a method for analyzing a social hierarchy. In contrast to approaches used for measuring status in organizations research, such as Bonacich's power centrality (Bonacich 1987; Podolny 1993; 1994; 2001; Podolny et al. 1996; Benjamin and Podolny 1999), Elo-rating is more appropriate for directed ties. Additionally, it is implemented dynamically based on the sequence in which interactions occur and continuously updates ratings by looking at interactions sequentially. There is no need to restrict analysis to defined time periods. This also allows one to assess the increase or decrease in an individual's status over time as well as the overall stability of the network. I measure order in terms of two emergent features of the hierarchy: 1) stability and 2) rank steepness. Stability reflects the frequency of rank changes over time. Rank steepness measures the disparity in rank scores across the hierarchy, as steep hierarchies mean upsets are less likely to cause overall rank changes.

To assess the stability of the rank order across time, I compute a stability index following McDonald and Shizuka (2012). The Stability Index is calculated as:

$$S = 1 - \frac{\frac{\sum_{i=1}^{d}(C_i \, x \, w_i)}{\sum_{i=1}^{d} N_i}}{2N} \tag{2}$$

where C_i s the sum of absolute differences between rankings on 2 consecutive days, w_i is a weighting factor determined by as the standardized Elo-rating of the highest-ranked individual involved in a rank change, N_i is the number of individuals present on both days, and N is the number of individuals in the group. Before division, values are summed over the desired time period, that is, d days.

To connect status to firm performance (Hypothesis 1), I follow Klepper and Sleeper's (2005) study of market evolution and estimate a logit model for the probability of a market entrant launching a spinoff. The dependent variable P_i equals the probability that over its lifetime, truck *i* spawned one or more brick and mortar restaurant spinoffs, and there is one observation for each of the 85 trucks in the sample. In total, seven trucks launched eighteen restaurants in the five years beginning May 5, 2010.

The covariates used in the model are time invariant and include the truck's rank in the status order (1 to 85) as well as controls to rule out alternative explanations. I include covariates for the number of Twitter followers at the end of the observation period, the order in which the truck entered the market, and whether the truck is itself a spinoff of an existing brick and mortar restaurant. As an alternative to status rank, I consider several other common measures of centrality from the social network literature: in-degree centrality (Freeman 1979), Bonacich power centrality (1987), eigenvector centrality (Bonacich 1972), and PageRank (Page et al. 1999).

Dyadic-level analysis.

The dyadic analysis examines the question of what predicts a mention between any two trucks in the network and whether that mention is reciprocated. I use two logit models. In the first model, I predict the presence of a mention between any two trucks during the one-year observation period (1 = mention occurred, 0 = no mention). The dependent variable is a binary indicator of whether or not a mention occurred between two specific trucks among all possible 7,140 dyads. I examine the effects of four dyad-level variables on the presence of a mention between trucks: the difference in the number of Twitter followers (Hypothesis 2), the presence of product competition (Hypothesis 3), the level of territory competition (Hypothesis 4), and whether the trucks share a commissary (Hypothesis 5). I control for the number of days both trucks were present in the market.

I use the data on food truck location choices to generate the measure of territory competition (Hypothesis 4). Competition for territory is measured as the Jaccard coefficient of contested vending territory between any two trucks. That is,

$$\frac{a}{(a+b+c)} \tag{3}$$

where a is the number of locations that truck A and truck B jointly serve, b is locations occupied by truck B but not by truck A, and c is locations occupied by truck A but not by truck B. Over the period November 21, 2008 – May 4, 2010 the 85 trucks park 17,951 times at 2,496 unique locations (mean 56.51 unique locations per truck, sd: 79.43). This measure is derived by rounding the geocodes to three decimal places, which aggregates the locations at a distance of 111 meters and reduces the number of unique locations from 2,496 to 1,775. I round the geocodes in this way so that trucks which park on the same block or at the same intersection are counted as sharing a location. I then create a two-mode adjacency matrix of the trucks and the locations they occupy. These data allow me to quantify the total number of locations in which a truck vends and, more importantly, which locations are served by more than one truck. I make the assumption that trucks that serve the same location are more likely to compete for customers. The Jaccard coefficient measures the proportion of territory overlap between any two trucks in the market. The values of the coefficient range from zero to one, where one is exact overlap.

In the second dyadic-level model, I predict whether a mention was reciprocated. The dependent variable is whether a mention was reciprocated within a one week time frame (1 = reciprocated, 0 = not reciprocated). In total, 931 mentions were reciprocated (40.6%). In addition to measures for the difference in Twitter followers (Hypothesis 7), product competition, territory competition, and sharing a commissary, I include an additional covariate: the order in which the mention occurred. This allows me to examine whether there is a time trend, with trucks becoming more likely to reciprocate as the market evolves (Hypothesis 6). I control for the number of days both trucks were present in the market.

Relational event model.

The model is based on the sequential form of Butts' (2008) relational event framework. Relational Event Models (REM) are a flexible framework for estimating sequences of what Butts calls "relational events," each of which represents a social action from an individual (the ‘sender’) towards one or more targets (the ‘recipient’) (2008, p. 159). Previous research has applied the REM framework to relational event sequences consisting of radio communications (Butts 2008), email communications (Quintane et al. 2013), and classroom interactions (DuBois et al. 2013). A relational event in my context is a Twitter mention ‘sent’ from a truck to another truck in the market. Each event is of the form $a = (i, j, t)$, where *i* is the sender, *j* is the recipient, and *t* is the time at which the event occurs. The framework assumes that each event is independent of all other events but conditional on the sequence of events that have occurred in the past. This conditional independence assumption implies that ‘‘past history creates the context for present (inter)action, forming differential propensities for relational events to occur’’ (Butts, 2008, p. 160).

To model the probability of the sequence of events, I specify the following model:

$$p(A|\beta, s) = \prod_{m=1}^{M} \frac{\exp\left[\beta' s\left(t_m, i_m, j_m, A_{t_m}\right)\right]}{\sum_{(i,j)\in \mathrm{R}} \exp\left[\beta' s\left(t_m, i, j, A_{t_m}\right)\right]} \tag{4}$$

where β is a vector of model parameters; $s(t, i, j, A_t)$ is a vector of statistics pertaining to the sender-recipient pair (i, j); $s(t, i, j, A_t)$ is a function of A_t, the sequence of all actions extending from time 0 up until time *t*; M is the number of events in the sequence; and Ω_R represents a set of events consisting of the event that occurred at time *m* and all possible events that could have occurred as the m_{th} event.

A relational event model can be represented as a conditional multinomial logistic regression (Butts 2008). I focus on the sequence of events and not on the precise time at which events occur. At each event or step in the sequence, the possible events are the set of possible pairs who may be linked as sender and recipient. For instance, if there were only three trucks A, B, and C in my data, then at each step in the sequence, there are only six possible events: the ties A-B, A-C, B-A, B-C, C-A, and C-B. The probability of each possible event within the set of possible events is conditional on the relational statistics computed from the prior sequence of events, and there are m x $(m-1)$ possible next events if m actors are potential participants in the next event. So if events 1:3 in the example sequence are ties from truck A to truck B, then the model accounts for the greater probability that the fourth event in the sequence will also be a tie from A to B. As such, the model predicts the existence of the next event in the sequence, based on individual attributes of the sender and recipient, attributes of the relation, and prior history of events.

The dependent variable for the relational event model is the choice of truck i to mention truck j. More specifically, given the truck-level and dyadic-level covariates, and a historical sequence of mentions, the dependent variable is the next event in the sequence. So for each mention in the sequence, the dependent variable is a binary variable containing the set of possible mentions (ordered pairs of sender and receiver trucks) and takes the value of 1 if the mention actually occurred between the trucks and 0 if it did not.

The independent variables capture the history of mentions between i and j as well as the history of their exchanges with all other trucks k. I compute measures for Preferential Attachment (Hypothesis 8), Reciprocity (Hypothesis 9), Persistence (Hypothesis 10), Recency (Hypothesis 11), and Triadic closure (Hypothesis 12). A definition of each of the variables is given in Table 1. I include dyadic control covariates. The dyadic controls adjust for features of particular dyads that may affect the likelihood of a mention. I control for the difference in the number of Twitter followers, the level of territory competition, product competition, selling complementary products, sharing a commissary, and sharing membership in a food truck owners' association. When users first log in to an online communication program like email or Twitter, it is common for them to go through their messages and reply to each, so I also control for batch sending behavior.

<Insert Table 1>

Results

Does Status Matter To Firm Performance?

Elo rating produced a status rank ordering with a stability index of .99 (Figure 4A). The stability index can range from 0 (completely unstable, with rank changes every day) to 1 (most stable). That the truck social hierarchy stability index is near 1 means that the rank orders (determined by continually updated Elo scores) rarely changed. This is illustrated in the rank trajectories in Figure 4A, which show that Kogi BBQ, the market pioneer, gains and holds the top position in the social hierarchy throughout the observation period. The highly stable social hierarchy means infrequent line crossing of the trajectories in Figure 4A.

<Insert Figure 4 Here>

There is no significant correlation between rank in the hierarchy and the number of Twitter followers on the last day of observation (-.14, p = .2). As the number of Twitter followers is largely a measure of the influence of a firm among customers, this indicates that the producing members of the market have different perceptions of the perceived status of trucks than do customers. From reading the Tweets sent by the various trucks, it appears that some owners are focused on building relationships with their customers while others are focused on building relationships with other trucks. Networking with other owners can help one to rise in the status hierarchy without experiencing a similar boost in recognition from customers.

As a null hypothesis test, I examine whether the observed social hierarchy is different from what could occur at random. I generate 1,000 random sequences of mentions, conditional on the same number of trucks (n = 85), level of activity (2,294 ties), and staggered entry of firms as in the observed data. From each random sequence, I generate a social hierarchy and compute the stability index (mean= .96, sd = .001) and the Elo rating of the winning truck (mean = 1,254; max=1,422; sd=37.88). Kogi's Elo rating (1,523) exceeds the maximum rating any truck earned under a random model (1,422) and thus deviates from the expected distribution. In other words, Kogi consistently wins at a higher rate than would be expected by random chance. In a random social hierarchy, each truck would have a 1.2% chance of winning (1/85 = 1.2%) and in only 11 (1.1%) of the random sequences does Kogi BBQ emerge as winner.

The Grubbs (1969) test for outliers indicates that the stability observed in the food truck market (.99) is significantly different from the expected distribution. For comparison, Figure 4B shows one of the randomly generated status hierarchies. The reduction in stability is evident from the greater number of crossed lines. It is worth noting that both the stability index for the random test and the observed stability index are very close to 1, meaning that the rank orders rarely changed. Recall that the stability index is calculated as 1 minus the ratio of rank changes per individuals present over a given time period, divided by 2 times the group size (equation 2). Therefore, an important attribute of any hierarchy is that it becomes more stable as the group size increases. Individuals' rank orders are interdependent, making it more difficult to change position in the hierarchy as the number of group members increases.

<Insert Table 2 Here>

Table 2 reports the results of the logit model, which estimates the probability of a truck launching a spinoff restaurant (H1). Model 1 includes only controls for the number of Twitter followers, the order in which the truck entered the market, and whether the truck is itself a spinoff of an existing brick and mortar restaurant. Model 2 adds the status rank measure and shows that status rank has a positive impact on the likelihood of spinoff. Adding the status rank measure significantly improves model fit over the model with only the controls (Δ -2LL = 8.15, df=1, $p < .01$). Interpreting the coefficient indicates that each additional increase in rank (i.e., moving up from third place to second place) is associated with a .3% increase in the probability of a truck launching a spinoff over a five-year observation window. Not surprisingly, the number of Twitter followers also had a positive effect, with each additional 1,000 followers being associated with a 1.3% increase in the probability of launching a spinoff. The order in which the truck entered the market was not significant. Models 3 through 6 test four common centrality measures from the literature as an alternative to status rank. None of these other measures is significant.

As a point of comparison, I follow Klepper (2009), and calculate the annual rate at which trucks spawn spinoffs by dividing the total number of spinoffs by the total number of years of production. I determine entry and exit dates for all 85 firms using the date of their first and last Tweet during the five year observation period. Collectively, these 85 firms operated for 375 years. Therefore, the annual rate at which firms spawned spinoffs was 18/375 = .05. As a comparison, Klepper (2009) observes an annual spinoff rate of .08 for the semiconductor industry as a whole over the period 1950-1986, with a spinoff rate for Silicon Valley firms of .13 and .02 for firms outside Silicon Valley. Klepper finds that the automobile industry has a rate of .04 during the years 1901-1924. In their study of the Italian tile industry, Cusmano and colleagues find an annual spinoff rate of .04 (2014). So while the number of spinoffs observed in my data is small, the rate at which spinoffs occur is similar to that observed in a range of other industries.

In summary, this first analysis provides empirical evidence that the food truck market is organized as a social hierarchy and that status matters for firm performance. I show that status rank is a better predictor than other centrality measures of the likelihood of a truck launching a spinoff restaurant.

How Do Firms In A New Market Acquire Status?

In the first analysis, I consider a Twitter mention to be a form of deference. Receiving a mention increases the status of the mentioned truck in the market. Next, I estimate models to investigate how trucks attract mentions and therefore acquire status in the market. Models 1 and 2 use a logit model to predict the likelihood of a mention between any two trucks in the market. Model 1 has only controls, while Model 2 adds variables for the difference in Twitter followers and the level of territory competition as well as dummy variables for trucks being direct competitors and selling complementary products. Model 2 is a significant improvement over Model 1 (Δ -2LL = 885.2, df = 4, $p < .001$). Models 3 and 4 use a logit model to predict the likelihood of a mention being reciprocated. The full model, model 4, is a significant improvement over the model with only controls, model 3 (Δ -2LL = 141.7, df = 5, $p < .001$). The pattern of results is similar across models.

<Insert Table 3 Here>

The difference in Twitter followers variable shows a consistent and significant effect across models. The negative coefficient in Model 1 indicates that mentions are more likely to occur when the sender has fewer Twitter followers than the receiver (H2). Conversely, mentions are also less likely to occur when the sender has more Twitter followers than the receiver. The positive coefficient in Model 2 indicates that mentions are more likely to be reciprocated when the sender has more Twitter followers than the receiver (H7). In other words, trucks with more Twitter followers are less likely to reciprocate mentions sent by trucks with fewer Twitter followers. The number of followers has a larger effect on the likelihood of a reciprocated mention than it does on the likelihood of a mention. If the sender has 10,000 more followers than the receiver, the likelihood of a mention increases by approximately 1% (exp[-1.07e-06*-10000] = 1.01). If the sender has 10,000 more followers than the receiver, the likelihood that the mention will be reciprocated within a week increases by approximately 9% (exp[8.42e-06*10000] = 1.09).

The effect of territory competition (H4) is positive and significant for both models. Trucks become more likely to mention and reciprocate mentions from trucks as the amount of overlapping territory increases. Trucks are also more likely to mention and reciprocate mentions from trucks that sell complementary products. The direct competitor effect (H3) is non-significant in Model 2, likely because I observe are a few mentions sent from competing Korean barbecue taco trucks to Kogi BBQ. The direct competitor effect is negative and significant in Model 4, indicating that the few times a truck mentioned a direct competitor, there was little likelihood of the mention being reciprocated.

Considering the other variables in the model, I find that the physical proximity afforded by sharing a commissary (H5) has an effect on interaction on Twitter. Trucks are more likely to receive mentions and have their mentions reciprocated when they share a commissary with the other truck in the dyad. The analysis also provides evidence of a time trend in the market—

reciprocity increases over time in model 4 (H6). So as the market grows, it becomes more likely for trucks to reciprocate mentions. The third analysis examines these time dynamics in more detail by modeling the emergence of social mechanisms. Taken together, the results of analysis 2 provide support for H1, H2, H4, H5, H6, and H7, but only partial support for H3.

What Social Mechanisms Emerge To Sustain The Social Hierarchy Over Time?

Maximum likelihood estimates for three models are presented in Table 4. The dependent variable is the next sender-receiver pair in the sequence. Model 1 contains control variables from the dyadic analyses and should be considered as a null model against which the explanatory power of the subsequent models can be compared. Model 2 introduces the social mechanisms preferential attachment, persistence, recency, reciprocity, triadic closure, and a control for batch tweeting. Model 3 combines the control variables and social mechanisms. Model 3 significantly improves model fit over model 1 (Δ -2LL = 8,916.8, df = 6, $p < .001$) and model 2 (Δ -2LL = 710.7, df = 6, $p < .001$). The results associated with my hypotheses are robust across these models. Given this, I discuss only the Model 3 results.

<Insert Table 4 Here>

Considering the control variables first, I find that the results are similar to the dyadic analysis. The parameter estimates indicate that trucks with fewer Twitter followers are more likely to send mentions to trucks with more Twitter followers. The level of territory competition has a positive and significant effect on the likelihood of a sender-receiver dyad being observed in the sequence. I also find positive and significant effects for selling complementary products and sharing a commissary. As in model 2 of the dyadic analysis, the direct competitor effect is non-significant.

As for the social mechanisms, I find that the preferential attachment mechanism (H8)—a measure of cumulative advantage—has the largest coefficient and is thus the strongest social mechanism. The second-strongest social mechanism is reciprocity (H9). The results also indicate strong positive effects for persistence (H10; the tendency for *i*'s historical focus on sending to *j* to be reproduced in future mentions from *i* to *j*) and recency (H11; the recency of receipt of mentions from *j* affects *i*'s future rate of sending to *j*). The triadic closure mechanism (H12), a measure of transitivity, (number of ties from *i* to trucks (*k*) and trucks (*k*) to *j* affects *i*'s future rate of sending to *j*) is positive and significant, but weaker than the other social mechanisms. These results support H8:H12.

As an additional measure of model fit, I calculate when model 3 is "surprised" –in other words, when does it encounter observations that are relatively poorly predicted (Butts 2014)? Examining the deviance residuals, I find that the full model beats chance 84.0% of the time. I also examine the match rate to see whether the event predicted most likely to be the next in the sequence is in fact the one that is observed. I find that the full model matches the sender 34.9% of the time and the receiver 12.4% of the time. Model 3 correctly predicts either the sender or the receiver in the sequence 38.7% of the time and both the sender and the receiver 8.6% of the time. In comparison, model 1, which only has the dyadic controls, correctly predicts either the sender or the receiver in the sequence 5.8% of the time and both the sender and the receiver 1.6% of the time. Thus, the deviance residuals provide further evidence that adding the social mechanisms provides a significant improvement in predicting the next action to occur in the sequence.

Discussion and Conclusion

The goal of this study is to conceptualize market creation as the establishment of a social hierarchy that helps firms to balance cooperation and competition. I show the salience of status as a governance structure in new markets, measure its effect on firm performance, and identify factors determining how firms gain status and how the hierarchy is stabilized over time. The findings provide four contributions.

First, prior research on market creation has shown that firms cooperate to gain legitimacy for new markets through an adjustment of norms, values, and regulation (Humphreys 2010). This study extends previous research by showing how firms manage competitive dynamics during the legitimation process. A key finding is the role of deference in helping firms to balance cooperation and competition. Triangulating multiple methods enhances the internal validity of my finding that within a social hierarchy, lower status firms defer to those with higher status. Firms also defer by avoiding interactions with their direct competitors.

While recognizing that asymmetrical market relations gives rise to the threat of opportunism (Heide 1994), previous research on strategic alliances and channels has largely looked to symmetrical rules of behavior, such as trust, as a means for firms to limit their vulnerability (Moorman et al. 1992; Morgan and Hunt 1994). In contrast, my research suggests that when firms are unequal, interactions are guided by asymmetric rules, such as deference. When one firm has more status, the other is by definition vulnerable. A lower status firm may lack the ability to create a mutual, trusting relationship with a competitor, but it can show deference. Previous research in management suggests that low status firms engage in asymmetric relationships in this way because they benefit from increased access to the resources available to higher status firms (Ahuja 2000; Kalnins and Chung 2006; Stuart et al. 1999). The results supplement previous research taking a sociological approach to markets (Giesler 2012;

Humphreys 2010), providing further evidence that market creation is a social, not merely economic, process. To understand how firms balance cooperation and competition—a long-standing puzzle in marketing (Coughlan 1985)—it is necessary to view markets not as winner-takes-all games but as social groups where deference plays a key role in diffusing tensions.

A second, related contribution is to the literature on governance in marketing exchanges. Extant research has largely looked at governance as a monitoring and enforcement problem at the dyadic level (Brown et al. 2000; Heide 1994; Gundlach et al. 1995), with more recent studies finding that alliances between competitors can benefit from the presence of a third-party monitor (Ho and Ganesan 2013; Rindfleisch and Moorman 2003). My research suggests that as a governance structure, a social hierarchy organizes behavior not only on a dyadic or triadic level, but also on a network level. Rules of conduct, such as deference, shape a firm's behavior in two general ways: directly, as obligations, establishing how one's conduct is constrained and, indirectly, as expectations, establishing how others are bound to act in regard to the individual (Goffman 1956). Considering a market as a social hierarchy, each firm has an obligation to defer to higher status firms; it also has the expectation that lower status firms will show it deference. As a governance structure, a social hierarchy connects all firms in a market, as each is linked through chains of obligations and expectations.

A third contribution is my demonstration that informal, directed ties between firms influence performance in a new market. While recognizing the strategic importance of interfirm relations, prior research on their financial impact has found mixed results: Swaminathan and Moorman (2009), Tuli et al. 2010, and Xiong and Bharadwaj 2011(2011) found a positive effect on performance and Wulf et al. 2001(2001) and Gu et al. 2008 observe a mixed effect. These mixed results in the literature may be because of measures used in previous research—for instance, Gulati and Higgins (2003) found that the number of strategic alliances a firm invests in does not have a significant effect on performance. This study provides some resolution to these mixed results by demonstrating that the value of interfirm relationships is not only the number of relationships but also their direction and the status of the firms involved. This finding extends prior relationship marketing research, which has generally assumed that ties between firms are mutual and undirected and has therefore focused on networks of complementary firms and their alliances. Such work adopts exchange and marriage metaphors to suggest that firms are connected through contractual and reciprocal ties (Morgan and Hunt 1994) rather than individuals whose shifting allegiances are influenced by group-level social processes. When markets are made up of a few, large, established firms, previous models based on dyadic relationships may be appropriate. However, processes that stabilize dyadic interactions do not operate as well when social groups grow larger (Boyd and Richerson 1988). If market creation is to be understood as a dynamic process, one that allows for a wide range of behaviors, evolving cast of actors, and interdependent relationships, then it comes to seem less like marriage and more like synchronicity—the emergence of spontaneous collective action across a social group (Werner-Allen et al. 2005).

A fourth contribution is to networks research in marketing. Previous research has shown that social networks are an important firm resource (Swaminathan and Moorman 2009). Yet the marketing literature has lacked an understanding of the mechanisms underlying these network effects and the process by which they change over time. This work provides a methodological innovation by introducing two new approaches for analyzing networks. First, in contrast to previous studies which have used a static measure of firm reputation, centrality (Swaminathan and Moorman 2009; Van den Bulte and Wuyts 2007), Elo-rating provides a dynamic measure of status, one that provides a better account of the sequence of interaction in a market. In table 2, I show that Elo-rating is a better predictor than four widely used centrality measures. Second, the relational event framework extends previous research identifying the importance of reciprocity in interfirm relationships (Achrol and Kotler 1999) by offering marketing researchers a toolkit that can measure the role of other social mechanisms that shape how firms select partners and gain position in a market.

Limitations and Further Research

This research is not without limitations. First, my focus is on firm performance as measured by launching a brick-and-mortar spinoff, not sales or market share. Although food trucks are private businesses and their market share is not publically available, further research could examine the role of status in other industries where additional performance metrics are available. Second, Goffman suggests that status originates from differences in the relative degree of deference, respect, and attention individuals receive from others (Goffman 1956). I use a Twitter mention as a measure of deference from peer firms and the number of Twitter followers as a measure of attention from customers. Additional research might further unpack Goffman's deference/respect/attention triad, finding additional measures for status. For instance, in many hedonic industries (food, beer, music, fashion, publishing) there is little overlap between the firms that are celebrated by the industry as tastemakers and the firms that gain the largest market share from customers. Here, I examine an industry where the highest status firm is also the most financially successful, but there are many industries where this is not the case. Status also has cultural dimensions (Bourdieu 1973) as well as quality dimensions (Podolny 1993) not fully considered by the present research. Examining in greater detail how consumer perceptions of status contrast with producer perceptions would be a worthwhile avenue for further research.

Third, the research did not examine all of the structural or relational factors that might moderate how a social hierarchy is organized. I expect that further research will examine what factors moderate my findings. Finally, there are mixed results in the literature about the benefits of early market entry. After controlling for status, I find no significant result for order of entry (Table 2) confirming the findings of Golder and Tellis (1993) among others. Thus far, research assessing the performance differences between pioneers and followers has largely looked to pioneering advantage as arising from the process by which consumers learn about brands and form their preferences (Carpenter and Nakamoto 1989). Future research might consider pioneering advantage not only as influence on consumer preferences, but also as arising from an ability to gain status among other firms.

Contributions to Marketing Practice

This study provides several implications for firms entering new markets. Although the importance of developing networks is widely acknowledged by entrepreneurs and marketing managers, there is little consensus amongst practitioners around whom one should be trying to network with, how, and to what end. A key takeaway is that a relationship is a directed tie that later can become a mutual tie. A good strategy is to begin with an act of deference. In the food truck market, the first mention is an offer from the Dosa Truck: "@kogibbq LooKin For CHeF RoY WaNNa CoOK Him SuM DOSAS at His SecRet Spot In CulveR LALAland." While it takes over three months for Kogi BBQ to respond, the result for the Dosa Truck is much better than for another truck, Big Roccs Wings. Big Roccs asks for a favor from another truck, "@BigMistasBBQ hey need you to follow me big homey." In response to a lower status truck asking it for a favor, BigMistasBBQ retweets BigRoccsWings' request, adding "I will when you stop asking folks to follow you and start tweeting." Here, the learning for managers is that one should not begin an interaction with a request. By showing deference or offering a gift, the giver can create a sense of obligation from the recipient that may lead to a reciprocal exchange. Big Roccs' strategy of initiating a relationship with a request is quickly rebuffed.

Additionally, this study suggests that firms should be marketing themselves not only to their customers, but also to their competitors. They should invest in strategies that build regard, esteem, or admiration for their firm from their peers. The qualities that generate esteem depend in part on the industry. In the gourmet food truck market, trucks were recognized not only for their success with customers, but also for their truck's appearance, creativity in the kitchen, ability to gain press, and win awards. In industries that value skill and have a craft ethos, such as food, fashion, engineering, programming, it may benefit firms to emphasize their talents. In other arenas, it may benefit firms to emphasize their technology or their impact.

In general, this article has set an agenda for thinking of firms as social actors and markets as social organizations. Few firms can go it alone, so marketing managers and entrepreneurs will be better able to grow and stabilize new markets if they recognize the interdependence of their firms and their competitors. By making connections between market dynamics and social dynamics, marketing scholars and managers will have a much richer toolkit for understanding and predicting behavior. The broader agenda for this stream of research is to introduce new quantitative methods to model and test classical theories of culture and social behavior, thus providing scholars and managers with a better understanding of how markets function.

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Figure 1: Number of active food trucks per day (red) and number of Tweets per day (light blue): November 2008- November 2012. Dark blue lines represents moving averages.

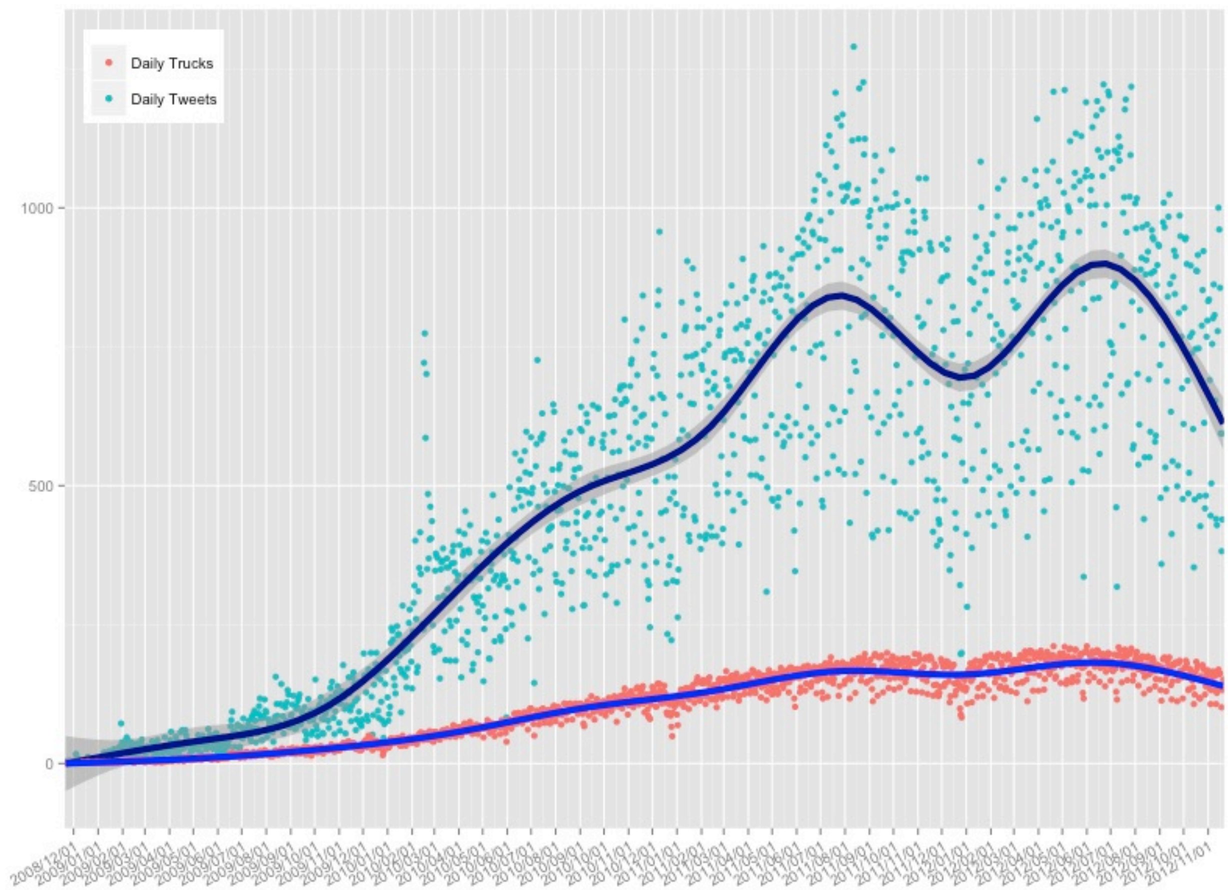

Figure 2: 2,496 unique locations used by food trucks between November 21, 2008 and May 5, 2010. Locations used only once are in red, those visited multiple times are blue.

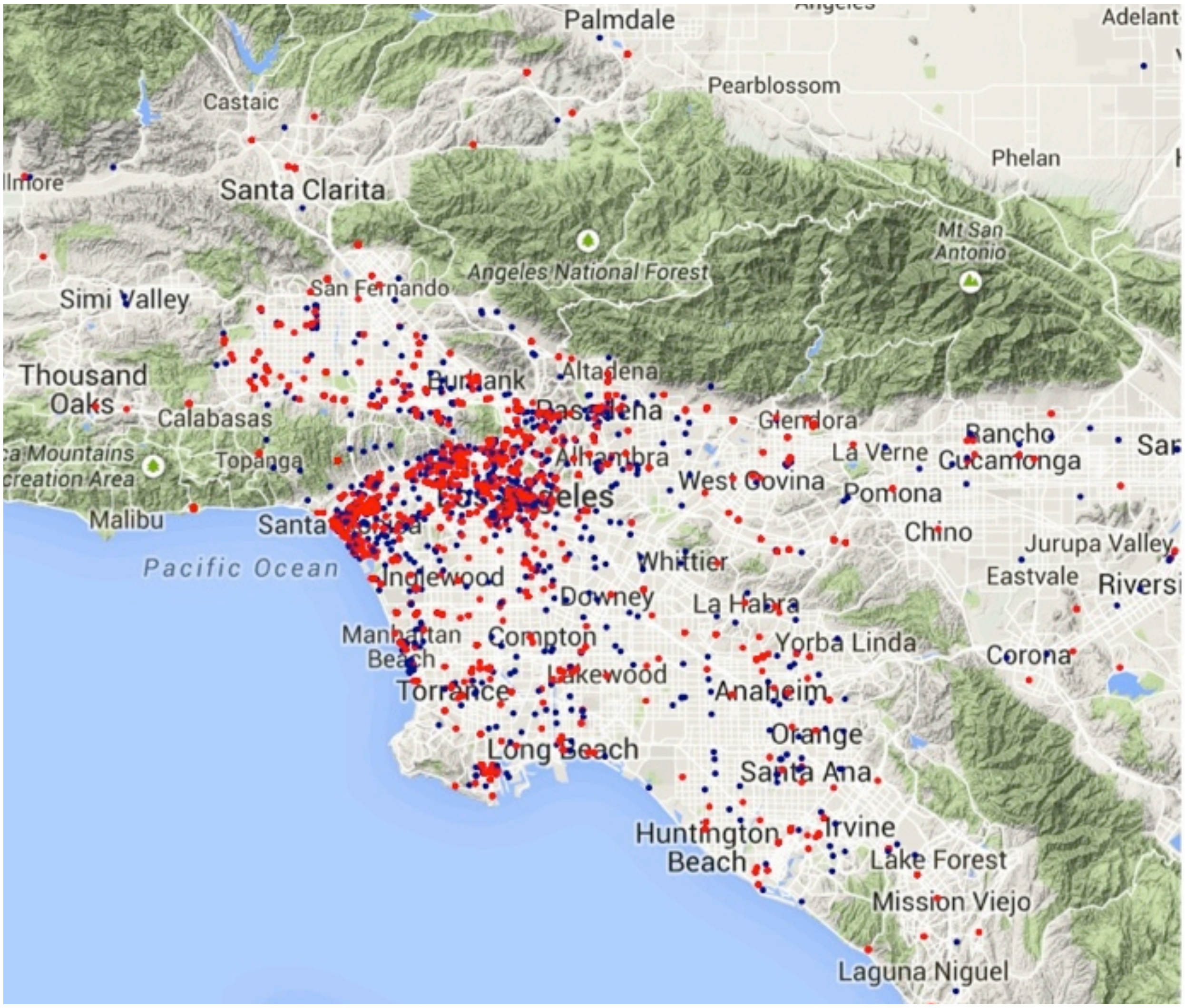

Figure 3: Example of obtaining commissary addresses from truck photos

Figure 4A: Trajectory of Elo-rating scores (y axis) over a series of contests (x axis). First 10 trucks are shown for clarity, with Kogi BBQ represented by #7. The data indicate a high stability index of 0.9857 over the course of 2,294 dyadic contests.

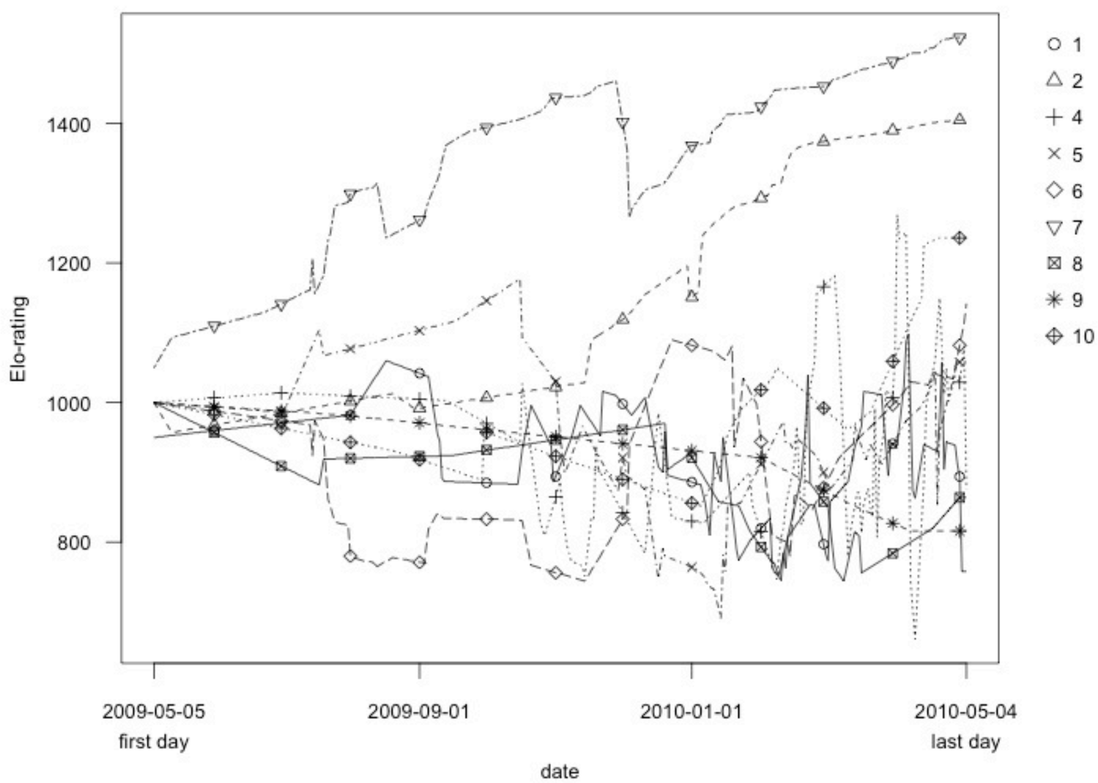

Figure 4B: Trajectory of Elo-rating scores (y axis) over a series of contests (x axis) from a randomly generated network with same size, activity, reciprocity, and delayed entry as in the observed data. First 10 trucks are shown for clarity, with Kogi BBQ represented by #4. Kogi's final position in the status hierarchy for this random network is #41. Stability Index of 0.959.

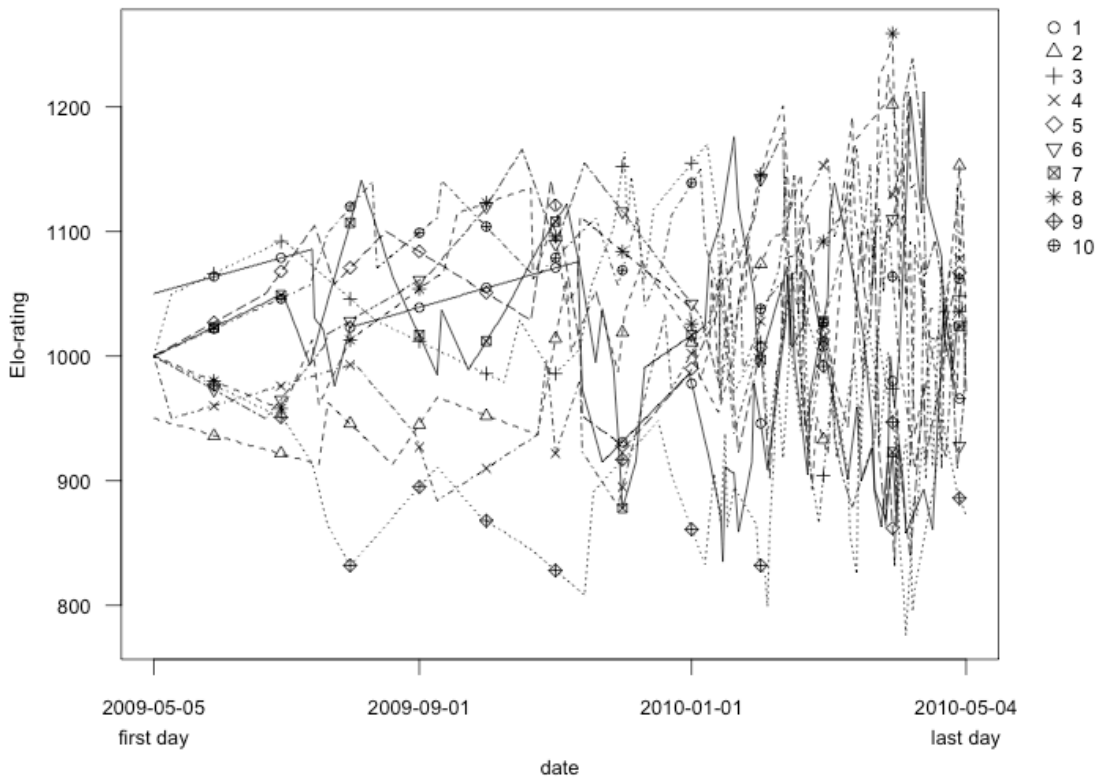

Table 1: Descriptive statistics and definitions of variables included in the analyses.

Variable	Measure	Mean	Min	Max
Status Rank	The truck's rank in the status hierarchy, as determined by a truck's Elo-rating score. 1= largest number of points, 2= second-largest, etc. A measure of a truck's prestige as determined by other trucks.	43	1	85
Order of Market Entry	The order in which the truck entered the market. 1= first, 2=second, etc.	43	1	85
Spinoff	The truck is a spinoff of an existing brick-and-mortar restaurant. (1=yes, 0=no)	.05	0	1
Number of Twitter followers	Number of Twitter followers as of May 5, 2010. A measure of a truck's prestige as determined by customers.	2,554.4	32	54,497
Difference in the number of Twitter followers	The difference in the number of Twitter followers between the sending and receiving trucks, as measured on the last day of the observation period (for dyadic models) or on each day (for REM models).	0	-79,242	79,242
Direct competitor	Whether two trucks in any possible dyad sell the same product. (1=yes, 0=no)	.004	0	1
Product complement	Whether two trucks in any possible dyad sell complementary products (as opposed to substitutes). For example, one sells tacos and the other ice cream. (1=yes, 0=no)	.29	0	1
Shared commissary	Whether two trucks in any possible dyad park at the same commissary. (1=yes, 0=no)	.10	0	1
Shared SoCalMFVA membership	Whether two trucks in any possible dyad are both members of the Southern California Mobile Food Vending Association, an industry advocacy group. (1=yes, 0=no)	.22	0	1
Territory competition	The Jaccard coefficient for degree of territory overlap between any two trucks. (1= identical vending territories, 0 = no overlap).	.03	0	.24
Reciprocity	An indicator variable for whether a mention sent from truck *i* to truck *j* is immediately followed in the sequence by a mention sent from truck *j* to truck *i*.	-	0	1
Batch Tweeting	A control effect to indicate whether a mention sent from truck *i* to truck *j* is immediately followed in the sequence by a mention sent from truck *i* to truck *k*. When users first log in to an online communication program like email or Twitter, it is common for them to go through their messages and reply to each. This effect controls for this batch sending behavior.	-	0	1
Recency	Truck *j*'s rank in the list of truck *i*'s most contacts. For example, if *j* is the last truck *i* had contact with, then *j*'s recency rank =1. This falls to ½ if *j* is the second most recent truck to have contacted *i,* et cetera.	-	0	1

Persistence	The number of mentions sent from *i* to *j* by time *t* divided by the number of mentions sent by *i* by time *t*	-	0	1
Preferential Attachment	The number of mentions received by *j* by time *t* divided by the number of mentions sent by all trucks (*k*) by time *t*	-	0	1
Triadic Closure	The number of mentions sent from *i* to trucks (*k*) and received by *j* from trucks (*k*) by time *t* divided by the number of mentions sent by *i* and received by *j* by time *t*	-	-	-

Table 2: Model estimates: probability of launching a brick-and-mortar restaurant

	Controls (1)	Status Rank (2)	In-degree Centrality (3)	Bonacich Power Centrality (4)	Eigenvector Centrality (5)	PageRank (6)
Status Measures						
Status Rank		-3.24e-03**				
		(1.14e-03)				
In-degree Centrality			-6.72e-04			
			(8.64e-04)			
Bonacich Power Centrality				-6.24e-03		
				(2.91e-02)		
Eigenvector Centrality					-1.44e-01	
					(1.62e-01)	
PageRank						2.37
						(2.95)
Controls						
Intercept	7.0e-02	2.02e-01*	9.22e-02	6.92e-02	9.45e-02	3.96e-02
	(6.6e-02)	(7.89e-02)	(7.24e-02)	(6.7e-02)	(7.19e-02)	(7.67e-02)
Number of Twitter Followers	1.4e-05**	1.25e-05*	1.57e-05**	1.39e-05**	1.59e-05**	1.08e-05
	(5.0e-06)	(4.79e-06)	(5.46e-06)	(4.99e-06)	(5.40e-06)	(6.32e-06)
Order of Market Entry	-4.4e-04	-1.87e-04	-6.10e-04	-4.19e-04	-6.43e-04	-2.10e-04
	(1.2e-03)	(1.2e-03)	(1.27e-03)	(1.26e-03)	(1.27e-03)	(1.28e-03)
Spinoff	-1.0e-01	-9.81e-02	-1.20e-01	-1.01e-01	-1.21e-01	-7.93e-02
	(1.4e-02)	(1.31e-01)	(1.39e-01)	(1.38e-01)	(1.39e-01)	(1.4e-01)
Null Deviance	21.69					
Residual Deviance	11.72	3.57	11.08	11.67	10.88	11.04
Observations	85	85	85	85	85	85

.p<.10 *p <.05 **p<.01 ***p<.001

Table 3: Model estimates: probability of a mention, probability of a reciprocated mention.

Variable	Hypothesis	Mention Controls (1)	Mention Full Model (2)	Reciprocated Mention Controls (3)	Reciprocated Mention Full Model (4)
Variables of Theoretical Interest					
Difference in Twitter followers	H2 (Mention) / H7 (Reciprocated Mention)		-1.07e-06*** (2.51e-07)		8.42e-06*** (1.14e-06)
Direct competitor	H3		.004 (.02)		-.19*** (.06)
Territory competition	H4		2.45*** (.08)		1.84*** (.22)
Product complement			.02** (.007)		.04* (.02)
Control Variables					
Intercept		-.2*** (.02)	-.02 (.02)	-.68*** (.1)	-.3* (.12)
Shared commissary	H5	.03* (.01)	.03** (.01)	.11*** (.02)	.14*** (.02)
Number of days co-present (logged)		.06*** (.005)	.004 (.005)	.18*** (.02)	.07** (.02)
Time trend	H6			1.38e-04*** (1.59e-05)	1.21e-04*** (1.56e-05)
Null Deviance		2962.01	2962.01	3247.1	3247.1
Residual Deviance		2799.41	1914.22	3114.9	2973.16
Observations		7140	7140	2294	2294

.p<.10 *p <.05 **p<.01 ***p<.001

Table 4: Model estimates: predicting the next event in the sequence

Variables	Hypothesis	Dyadic Controls (1)	Social Mechanisms (2)	Dyadic Controls + Social Mechanisms (3)
Dyadic Controls				
Difference in Twitter Followers		-3.21e-05*** (3.13e-06)		-9.74e-06** (3.17e-06)
Territory Competition		21.28*** (.35)		10.73*** (.44)
Direct Competitor		-.12*** (.10)		-.3.18e-03 (.12)
Product Complement		.65*** (.04)		.19*** (.05)
Shared Commissary		.93*** (.05)		.40*** (.05)
Shared SoCal MFVA Membership		.39*** (.04)		.44*** (.05)
Social Mechanisms				
Preferential Attachment	H8		7.0*** (.32)	4.70*** (.34)
Reciprocity	H9		3.38*** (.10)	3.23*** (.10)
Persistence	H10		2.0*** (.12)	1.63*** (.14)
Recency	H11		2.90*** (.06)	2.60*** (.06)
Triadic Closure	H12		.06*** (.002)	.04*** (.002)
Batch Tweeting			3.94*** (.05)	3.75*** (.05)
Null Deviance		40,711.47		
Residual Deviance		36,312.09	28,106.06	27,395.33
Observations		16,379,160	16,379,160	16,379,160

.p <.10, *p<.05,**p<.01,***p<.001

ESSAY 2:

What Drives Food Truck Location Decisions?

Social Contagion in Mobile Location Choice

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1. *Introduction*

Marketing has long been interested in the question of how firms make market entry and location choices. A retailer faces two key questions: (1) Should it enter a particular market (entry decision), and if so, (2) Where within the market should it locate its new store (location decision). Mobile retailers, such as food trucks, are an interesting phenomenon because a location choice is a temporary commitment. Mobile retailers thus face a third question: (3) Should it revisit a previous location or choose a new location (relocation decision). In this paper, we study the location decisions of gourmet food trucks in Southern California. Gourmet food trucks post their locations on Twitter to inform their customers, however, their competitors can then also observe their location choices. It is therefore possible to explore how information on rivals' choices affects firm strategies—specifically, decisions on whether to try a new location or revisit a previously used location.

Researchers in marketing, management, and sociology have long studied how innovations diffuse through populations. An important theory is that the diffusion of innovation may be driven by social contagion. In other words, individuals' adoption behavior is influenced by their exposure to other individuals' knowledge, attitudes, or behavior regarding the innovation. Many studies have documented the presence of social contagion in consumer adoption of new products (for a review see Iyengar et al. 2011a) and established that multiple sources of information influence product adoption (Narayanan et al. 2005; Hu and Van den Bulte 2014); researchers are now moving from investigating whether contagion influences product adoption to how and why it occurs (Aral 2011; Godes 2011).

Researchers have also found evidence of social contagion in the market entry and location choice decisions made by firms (Bronnenberg and Mela 2004; Shen and Xiao 2014).

Research suggests that before choosing a location, a firm lacks information about the location's profitability and thus resolves this uncertainty by observing the location choices of previous entrants. However, while demonstrating that social contagion influences firm behavior, research in this area still lags behind studies of product adoption behavior. Extant research has neither modeled the exact mechanics of information transmission among firms nor empirically distinguished between alternative channels of transmission. Further, for mobile firms, choosing a location does not mean that it will keep using it. Thus, several important questions remain unanswered. What sources of information influence location choice? Can social contagion affect not only location choice but also repeat behavior? If so, are those who influence firms to choose a location the same as those who influence firms to repeat a location choice? If contagion operates differently at each stage, can we gain some insights about why this happens?

The presence of social contagion in repeat location choice may appear puzzling. Why would firms' subsequent behavior be affected by peers, since trying a location provides the opportunity to resolve the uncertainty about its profitability? We consider four main factors that have been shown to affect product adoption: information transfer, normative pressures, competitive concerns, and performance network effects (Van den Bulte and Lilien 2001). Here, we extend these four factors to location choice. First, firms may acquire information that changes their prior beliefs about the profitability of a location. Second, firms may be influenced by normative pressures, resulting in them modeling their behavior after proximate peers. Third, competitive concerns may impel a firm to avoid locations visited by direct competitors or the market pioneer. Fourth, other firms' choices may produce performance network effects—in other words, multiple firms co-locating increases consumer demand and makes a location more attractive. To account for these factors, we developed a model of social contagion that allows us to (i) distinguish the source of the information passing to a firm, and (ii) distinguish whether the information is received by an experienced firm versus a firm with no prior experience at a location.

Measuring social contagion is difficult for two major reasons. First, it is difficult to define the set of peers or neighbors from whom an individual can learn (Conley and Udry 2010). Direct data on information transmission is generally unavailable to researchers studying market entry. Consequently, extant studies of social contagion have typically made assumptions that relate observed relationships between firms—such as geographic proximity—to unobserved flows of information. Second, even with a proper definition of a firm's peer set, distinguishing social influence from other phenomena that may give rise to similar observed outcomes is problematic. In the absence of contagion, a firm may act like their peers as a result of interdependent preferences or because they are subject to related unobservable shocks.

We have collected data to address these two issues. Our study combines individual-level location choice data, social network data, Census data, and brick-and-mortar restaurant data to investigate the presence and nature of contagion in mobile location choice during the first year of the gourmet food truck market.

For the first issue, our data allow us to model the peer set and the transmission of information directly, rather than relying on a proxy, such as the number of adoptions in each previous time period. Within the gourmet food truck market, firms use Twitter to announce their locations to their customers as well as their peers. They are also required to park nightly at shared commissaries. We were thus able to collect detailed information on whom individual firms observe and know and use this to define communication ties.

Second, once information links are defined, the identification of contagion is still a formidable problem, as the fact that a firm chooses a location soon after their peers have done so might be a consequence of some unobserved variable. Rather than aggregating behavior into time periods, our strategy for identifying contagion relies on exploiting the specific timing of location choices to identify opportunities for information transmission. The staggered location announcements in our data naturally provide a sequence of time steps where new pieces of information regarding the profitability of various locations may be revealed to the firm. We then examine whether this new information is associated with changes in a firm's location choices in a manner consistent with social contagion. As we use information about the sequencing of the location choices, we can avoid the standard problems of non-independence of observations that affects network analysis and model the probability of one location choice happening conditional on covariates that include prior states of the market.

Our contribution consists of two theoretical contributions and a methodological contribution. First, while early spatial competition models allowed for costless relocation (e.g., Hotelling 1929; Chamberlin 1933), subsequent empirical research has generally assumed that location decisions are permanent. Our study thus provides evidence on a fundamental issue in marketing: how do firms react to their competitors when they can easily relocate? What we find is that their location decisions are highly responsive to the choices made by their peers in a manner consistent with social contagion. Further, this is true both when firms try new locations as well as when they repeat previous choices.

Second, we draw from theories of contagion in product adoption (Van den Bulte and Lilien 2001) and distinguish the sources of information at work in firm contagion. While we observe contagion operating in different ways across location choice and repeat behavior, the general pattern of results is consistent with previous research on market entry and expansion (Shen and Xiao 2014) suggesting that the underlying mechanism is uncertainty—firms are susceptible to the influence of others when uncertain about the potential profitability of a location and therefore less susceptible during repeat location choice.

Third, our statistical approach uses a relational event framework (Butts 2008), which is a departure from event history analysis, the standard technique for modeling social contagion in marketing, sociology, and economics (Iyengar et al. 2011b). Event history analysis aggregates behavior into monthly or yearly intervals, then analyzes for each person-time period observation, whether the person adopted the innovation at that time and how many of their network partners have adopted it (Valente 2010). This approach does not typically observe the flow of information during each time period in the study. Rather, the analysis uses a static measure of each individual's network and their time of adoption and then constructs data to replicate what happened over time. Our data and relational event approach allow us to model contagion processes directly, rather than assuming a static network or aggregating behavior into time panels.

The results are of general interest. As gourmet food trucks have diffused across California and many other US states, much of the media coverage has focused on the conflict between food trucks and brick-and-mortar restaurants. A wide-held assumption is that food trucks "poach" customers, so brick-and-mortar restaurants need protection in the form of regulations that control where food trucks can park (Needleman 2012). However, our results show that the location choices made by a truck's peers are a stronger influence than the presence of brick-and-mortar restaurants in driving a truck's decision to choose a location. We suggest that while much media attention has been paid to gourmet food trucks' innovative cuisine, their conflict with brick-and-mortar restaurants, and their interactions with customers on Twitter (), owners' relationships with each other are a substantial factor in driving the creation of this market, one that has been largely overlooked.

We first proceed by further developing the research questions, building on theories and findings from economics and sociology. We then describe the research setting, data, and modeling approach. We then present the findings and discuss the implications for theory, research, and practice.

2. Research Questions

Though social contagion and relocation have each been the subject of prior research, there is little research studying them jointly to build on. So we rely primarily on theoretical arguments to develop our research questions. We first briefly describe prior research on relocation. We then discuss informational influence, normative influence, competitive influence, and agglomeration as distinct contagion mechanisms. This provides the basis for refutable hypotheses on how and why contagion operates differently in location choice versus repeat location choice.

2.1 Prior Research on Social Contagion in Location Choice versus Relocation

Relocation is different from market entry or expansion because it involves giving up one location in favor of another. Prior research on social contagion focuses only on market entry, market expansion, or location choice and does not consider the repeated decisions made by mobile firms. Modeling firm location choice has a long history in marketing and economics and early theoretical models allowed for costless relocation (e.g., Chamberlain 1933; Hotelling 1929). However, to the extent that empirical research has studied relocation behavior, it has done so in the context of firm responses to government regulation and has not considered contagion.

Several recent studies have found evidence of social contagion in studies of the market entry and location choice decisions made by brick-and-mortar chain retailers. The standard entry model (e.g., Dixit 1979) predicts that a firm will choose a market without a competitor over one with a competitor. In contrast, more recent entry models which incorporate firm learning (Baum et al. 2000; Sault 2006; Shen and Xiao 2014; Toivanen and Waterson 2005; Yang 2012) have found that a rival's presence increases the probability of entry. Much of this research has explored the location choices of expanding chain retailers.

We expect that a market made up of mobile firms may be impacted by contagion in a different way than expanding chains choosing where to open new outlets. Specifically, a single-entity mobile firm is more responsive to market conditions and relies on different sources of information. Managers of brick-and-mortar chain retailers utilize a combination of in-house researchers and outside advisors to give them confidence in their decisions. These resources mean that learning likely plays a smaller role—in a study of Canadian fast food chains, Yang (2014) estimates that social contagion accounts for at most 5% of the decisions after controlling for other market characteristics. Single-entity mobile retailers like food trucks lack these resources and advisors. Research on herding among financial analysts suggests that analysts at smaller brokerages with fewer resources are more likely to follow the decisions made by others (Clement and Tse 2005). Lacking sophisticated market analyses to give them private information about potential locations, we therefore expect that mobile retailers would rely more on information they can obtain from peers.

2.2 Social Contagion Mechanisms Relevant for Location Choice versus Relocation

Lacking data on network ties between firms, prior research on social contagion in market entry and location choice has not fully specified the nature of the contagion process. Researchers studying contagion in product adoption have had more detailed network data (e.g., Iyengar et al. 2011a). Drawing from this literature suggests that peer influence can come from four different sources: informational influence, normative influence, competitive concerns, and performance network effects (Van den Bulte and Lilien 2001). Here, we adapt these four sources to exploring firm behavior.

2.2.1 Informational Influence in Location Choice versus Relocation

Informational influence, also referred to as social learning, is a process through which information observed from others changes one's prior beliefs. Before entry, firms face uncertainty because they lack information about the profitability of a location. However, they can observe the decisions of previous market entrants, allowing them to infer the profitability of a market or a location by learning from others (Baum et al. 2000; Caplin and Leahy 1998). Prior research on the fast food industry has demonstrated informational influence in contexts including McDonald's and Burger King in London (Sault et al. 2006), Canadian fast food chains (Yang 2014), and KFC and McDonald's in China (Shen and Xiao 2014).

Informational influence is less likely to affect the decision to revisit a location because a firm learns through entry (Yang 2012), lessening its uncertainty about the profitability of a location. Informational influence decreases with the decision makers' self confidence in their judgment (Iyengar et al. 2011b). Outside of marketing, studies of stock market analysts suggest that more experienced analysts are less prone to be influenced by the choices made by others (Hong and Kubik 2003). Empirical models of location choice in fisheries suggest that fishers have a tendency for 'inertia,' maintaining their patterns of fishing location choice over time rather than switching locations in response to information gathered from other vessels (Holland and Sutinen 2000).

Thus we would expect that in repeat location choice, a firm's personal experience and habits may substitute for input from peers. Yet while diminished, some peer influence may remain in relocation. Learning from entry may be slow when a firm has spent only a few hours at a location. For instance, a location near a stadium may have been bad during the off season but is now great during game days. Market conditions may change, leading to new uncertainty and a return to reliance on the judgment of peers.

So we expect that social contagion from informational influence would: (i) have a positive effect on location choice, (ii) originate from a firm observing the behavior of other firms in the market, (iii) be lower for firms with lesser uncertainty and thus be stronger in location choice than in repeat.

2.2.2. Normative Influence in Location Choice versus Relocation

Social contagion through normative influence stems from colleagues and group members (Iyengar et al. 2015). Mobile vendors (Sherry Jr 1990) and brick-and-mortar firms (Kalnins and Chung 2004) alike seek out relationships with other firms. Adhering to social norms provides new firms in emerging market categories with legitimacy (Humphreys 2010).

The extent to which firms conform to social norms surrounding location choice is likely to vary with the firm's experience. Previous research suggests that individuals with greater self-doubts are more susceptibility to normative influence (Chang and Arkin 2002). Normative influence is therefore more likely to affect the decision to try a location rather than the decision to revisit it. Without any experience at a location, a firm has little to lose by imitating colleagues. However, once a firm has tried a location, they have private knowledge of its profitability and more to lose if imitating colleagues is not a profitable strategy. While individuals can face social disapproval for deviating from norms, they likely value their own profit over the approval of their peers.

The considerations of normative influence thus lead us to expect that social contagion from normative influence (i) has a positive effect on location choice, (ii) originates from group members or proximate peers, (iii) has a positive but less pronounced effect on repeat location choice.

2.2.3. Competitive Influence in Location Choice versus Relocation

Previous research on social contagion in product adoption suggests that contagion can operate through concerns that not adopting may result in a competitive or status disadvantage (Burt 1987; Hannan and McDowell 1987). Here we distinguish between two sources of competitive influence relevant to a firm: direct competitors and the market pioneer.

Since Hotelling (1929), there have been numerous studies on how product differentiation affects spatial competition. Empirical models suggest that to lessen competition, firms selling substitutable products differentiate based on a product attribute (Mazzeo 2002) or geographic location (Seim 2006). Previous studies of location in the fast food industry have found that Burger King and McDonald's are more profitable when they avoid close competition (Thomadsen 2007). This suggests that a firm would avoid choosing a location used by a competitor.

In relocation, the same logic would apply: if a firm avoids trying a location used by a competitor, then they would also avoid repeating a visit to a location used by a competitor. If in consumers' eyes two firms offer essentially undifferentiated products, direct competitors would avoid each others' preferred locations, as consumers may have developed a preference for the first firm to use the location. The considerations of competitive influence thus lead us to expect that social contagion from direct competitors (i) has a negative effect on location choice, (ii) originates from firms selling a similar product, (iii) also has a negative effect on repeat location choice.

In addition to direct competitors, firms are also likely to observe the choices of the market pioneer when making location decisions. The literature on first-mover advantages suggests that the first entrant chooses the most attractive location in the market (Kerin et al. 1992). The second mover, to lessen competition, chooses a location away from the first mover. However, if the second mover is a strong competitor, it will not be afraid of locating next to the first-mover (Tyagi 2000).

This suggests for our context, that firms should have a general tendency to avoid locations preferred by the first mover. However, if firms are strong competitors and choose a location used by the market pioneer, they should have a preference for those locations, as the presence of the pioneer suggests that it is the best location in the market. Considering the competitive influence of the market pioneer, we would expect that social contagion (i) has a negative effect on location choice, (ii) originates from the first entrant to the market, and (iii) has a positive effect on repeat location choice.

2.2.4. Agglomeration in Location Choice versus Relocation

Social contagion can operate through a network effect, where the benefits of use—and thus the benefits of adoption—increase with the number of prior adoptions (Van den Bulte and Lilien 2001). In the context of location decisions, this network effect is agglomeration. In characterizing the above four conduits for social contagion, we have considered a market where only one firm at a time can use a location. But there are locations in the gourmet food truck market where we observe multiple firms co-locating or parking together at the same time. As firms co-locate, they draw more customers to a location, making it increasingly attractive. The profitability of choosing the location increases with the number of other firms (Marshall 1920). When considering a potential location, if a firm observes multiple other firms at the location, this is a stronger signal of demand than observing only one firm at the location. This strong signal would be attractive to a firm that has not previously chosen the location and thus has uncertainty as to its profitability. However, if a firm has prior experience at a location, it would have less uncertainty as to its potential profit. Considering agglomeration effects, we would thus expect that social contagion (i) has a positive effect on location choice, (ii) originates from other firms choosing the same location on the same day, and (iii) has a less pronounced positive effect on repeat location choice.

2.3 Hypotheses

The theoretical arguments leads to five predictions for location choice and repeat location choice (Table 1):

<Insert Table 1 Here>

3. Research Setting

To facilitate our subsequent model exposition, we describe the industry from which we have data, discuss how location choices are made for retailers in this category, and illustrate how retail distribution evolves across space as well as time.

3.1 General Description

3.1.1 Consumers.

The food truck industry accounted for roughly $857 million in sales in the year 2014 in the United States. The market for food sold by food trucks has increased at an annual rate of 9.3% per year between 2010 and 2015, making it one of the fastest growing sectors of the food industry. Food truck product consumption tends to be higher in warmer and urban regions than elsewhere in the United States (Alvarez 2015).

3.1.2 Products.

Before 2008, most firms in the food truck industry were ice cream trucks or *loncheras*, the so-called traditional taco trucks. Kogi BBQ, a Southern California company, is widely credited with creating the gourmet food truck segment. Launched in November 2008, Kogi BBQ introduced several innovations, most notably a Korean BBQ taco that offered customers higher quality ingredients and a fusion of Korean and Mexican flavors. In contrast to ice cream trucks, which used music to announce their locations, and traditional taco trucks, which had fixed locations and schedules, Kogi used Twitter to announce its location to its customers. Kogi choose Twitter for pragmatic reasons. According to their marketing consultant, Mike Prasad, they needed a tool to drive repeat business while solving “the problems of being a mobile venue” (Mohajer 2009). This innovation allowed Kogi to change locations several times a day. As Kogi BBQ gained popularity and media attention, over 500 firms followed it into the Southern California market, with over 3,000 launching nationwide.

3.1.3 Food Truck Location Choice Process.

We interviewed twelve food truck owners in Southern California and reviewed interviews with Kogi BBQ’s co-founder, Roy Choi, to learn how they chose locations. Early in the development of the market, pioneers including Kogi BBQ went through a period of fly-by-night experimentation, where they found new locations by driving around, choosing an empty parking lot or sidewalk, and then announcing the location on Twitter. Choosing a location in this way might have worked with customers, but it occasionally landed owners in trouble with zoning restrictions or health code regulations. In interviews, owners described indicators they used to assess the potential profitability of a location, such as driving distance, availability of parking, income level of the neighborhood, foot traffic, and the density of brick-and-mortar restaurants. They sometimes scout potential locations from a personal vehicle or Google Street View before bringing the truck. As more firms entered the market, owners began using the information provided by the location choices of their peers. To decide whether to enter the market, later entrants visit locations used by earlier entrants and count the number of customers in line at their truck to estimate potential profit. Owners also look at the Twitter feeds of other trucks to see where they go and then park there on the nights when they are not there.

Owners characterized finding a profitable location as a trial and error process. When a choice is successful, an owner described it as "like a remote control for business, Tweet and 30 people show up immediately." However, not every choice is successful. Even if a truck has parked at a location several times before, there is still uncertainty as the number of customers may vary due to factors including the day of the week, weather, season, and level of competition. Many owners try to predict the number of customers and use this estimate to guide how much food to prepare in advance. With their limited storage and cooking space, food trucks face capacity constraints, so owners lose money when they prepare too much or too little food. This additional risk adds to the difficulty of correctly assessing the profitability of a location. When situations are characterized by high uncertainty and high complexity, research suggests that potential adopters are likely to turn to opinion leaders for guidance (Hahn et al. 1994). Considering how much uncertainty remains even when owners do have experience at a location, it is likely that they rely on their peers' judgments both before using a location for the first time and then later in considering future visits.

3.2 The Development of the Gourmet Food Truck Market in Southern California.

By tracking Kogi BBQ's entry path, we find that the market pioneer's initial locations were near bars in neighborhoods with night life such as Hollywood, Santa Monica, and Silverlake. From there, Kogi visited the campus of UCLA and then quickly began to explore other cities in Los Angeles County, before venturing further to Orange County, which is more affluent than the rest of Southern California. By the end of the first year, Kogi has opened a second truck and parked 1,589 times at 389 unique locations. For 335 (86.1%) of those locations, Kogi was the first gourmet food truck to use the location. Figure 1, Panel A illustrates the diffusion of Kogi's locations across Southern California.

In contrast to Kogi's wide-ranging exploration, later entrants were relatively more conservative. The average follower firm parked at 26.5 unique locations and pioneered only 12.6 locations. An alternative to Kogi's exploration strategy is to 1) use locations developed by other trucks and 2) choose fewer locations and repeat more visits there in order to build up a more localized customer base. In contrast to Kogi's 389 unique locations, the second most active truck, Calbi BBQ, parks 579 times at only 90 unique locations, but focuses 100 (17.3%) of their visits on just three locations. Figure 1, Panel B illustrates the diffusion of Calbi BBQ's locations across Southern California.

<Insert Figure 1 Here>

During the first year of the gourmet food truck market, the 49 trucks not only expanded to 151 cities in Southern California but also continuously increased the number of locations and visits in the cities they had already entered. Such rapid expansion contributed to the public perception of a food truck phenomenon. Figure 2 shows the diffusion of locations over Southern California. Over the first year, the 49 trucks made a total of 5,391 location choices. An average of 6.2 trucks parked each day with 40 days in which no food trucks were observed vending and a maximum of 25 trucks vending on a single day. As Figure 3, Panel A shows, the number of trucks and locations increases over time. Figure 3, Panel B shows the number of trucks active each day.

<Insert Figures 2 and 3 Here>

We define a repeat visit as returning to a location visited by the truck at any time in the past. Figure 4 shows the number of locations and number of repeated locations for each truck in the market. Kogi BBQ tries 389 locations and repeats 165 of them (42.4%). Considering the other trucks, each follower firm tries 26.5 locations on average and repeats 11 of those on average (41.5%). More than half (54.9%) of the 941 locations were not repeated during the observation period. Out of the 941 locations, 111 (11.8%) were repeated once, so only 313 (33.2%) of the locations had three or more visits. The most popular location, on Abbot Kinney in Venice, had 243 visits by 16 different trucks.

<Insert Figure 4 Here>

Most trucks return multiple times to the same locations. In interviews, gourmet food truck owners described their location strategies as more calculated than that of traditional taco trucks and road trucks. Many traditional taco trucks park at one location, becoming like a mini brick-and-mortar restaurant. Road trucks travel from construction site to construction site, stopping for a few minutes at each to sell food to workers (Huus 2011). In choosing when to repeat a visit, gourmet truck owners commented that they preferred to repeat visits irregularly, rather than on a set schedule. By not having a predictable schedule, a truck's visit to a location can be perceived as a limited-time offer that lures in customers. This approach has some parallels in other seasonal or limited-time products in the food industry, such as Starbuck's Pumpkin Spiced Latte and McDonald's elusive McRib sandwich.

4. Data

The data cover the location choices of all 49 gourmet food trucks operating in Southern California over a period of 12 months from the time of Kogi BBQ's launch in November 2008. The data consists of (i) the sequence of location choices as announced on Twitter by all of the trucks in the market, (ii) location characteristics, including population, median income, and density of brick-and-mortar restaurants, and (iii) truck characteristics, including commissary address, timing of market entry, product category, number of Twitter followers, and several other characteristics.

4.1 Twitter Data

We define the study population as gourmet food trucks in operation in Southern California during the 12 month observation period. We define a gourmet food truck as a firm that operates from a truck and uses Twitter to interact with customers. We obtained lists of food trucks including name, product category, and Twitter user name from two industry databases—RoamingHunger and FoodTruckMaps. A Twitter data reseller, GNIP, provided all of the Tweets from each of the trucks, 18,212 Tweets in total. Using Natural Language Processing in Python, we extracted the addresses of the locations announced in the Tweets. We then geocoded the addresses and aggregated the locations at a distance of 100 meters – in other words, every longitude, latitude point within 100 meters was counted as the same location. As trucks often advertise a visit to a location multiple times, we dropped repeated announcements. We identify each truck with at least two location announcements during the one year period beginning November 20, 2008 as our study population. We identified 941 locations visited by 49 trucks meeting this criterion. After transformation, the data is a time-ordered sequence of truck-location dyads:

<Insert Figure 5 Here>

4.2 Location Characteristics

We collected zip code-level characteristics from the US Census Bureau's 2010 American Community Survey for each of the locations. For each of the 941 locations in the data, we observe the population density and median household income. During the growth of the gourmet food truck market, many brick-and-mortar restaurant owners complained about unfair competition from food trucks with lower overhead (Simmons 2009; Dermer 2011). To investigate whether food trucks had a preference for locations near brick-and-mortar restaurants, we obtained a dataset of the street addresses of all brick-and-mortar restaurants in California from restaurant-data.com, which we then geocoded. Using the longitude and latitude information for each location and each brick and mortar restaurant, we calculated the number of brick-and-mortar restaurants in a .5 mile radius of each food truck location.

While in theory a food truck can park and vend anywhere, in Southern California, owners face significant regulations. Trucks must have health permits for each county and business permits for each city with jurisdiction over a location. One owner reported maintaining 35 separate permits. Some cities also have restrictions on where, when, and for how long trucks can operate. We collected the city and county for each of the 941 locations, then identified which cities and counties had more burdensome regulations during the observation period using data provided by the Southern California Mobile Food Vendor's Association, an industry advocacy group. Specifically, we identified twelve cities and two counties where the SoCal MFVA had either overturned restrictions or failed to overturn restrictions after the observation period.

4.3 Commissary Addresses

Food trucks are required to park nightly at commissaries, which are garages with shared cleaning, food preparation, and storage facilities. The address of the commissary that each truck uses is stenciled on its side. Using Google Images, we found photos of the food trucks, which we then used to obtain the geographic location of each truck's commissary. The 49 trucks park at 19 commissaries. To cross-check the accuracy of the information, we obtained Los Angeles Health Department inspection and permit records, which contain the commissary address of the truck. The information from the two sources is highly consistent, which ensures the quality of the data. Using the longitude and latitude information for each commissary allows us to track the distance between each vending location and the trucks' headquarters or any other location in the network.

Following Iyengar and colleagues' (2015) study of social contagion among physicians, which used the hospital where the physician worked to identify sources of normative influence, we use the commissary where each truck parks to identify the owner's immediate colleagues. Prior research on normative influence suggests that norms often spread via face-to-face interaction (Goffman 1959). In the interviews, owners describing learning business practices, including potential locations, by observing and interacting with other owners at their commissary. Of the 49 trucks in our data, 37 park at a commissary shared with at least 1 other gourmet food truck.

5. Data Analysis Approach

We analyze how contagion affects location choice using a relational event model (Butts 2008), which is a new class of social network models for investigating dynamic networks.

5.1 Relational Event Model

Relational Event Models (REM) are a flexible framework for estimating sequences of what Butts calls "relational events," each of which represents a social action from an individual (the 'sender') towards one or more targets (the 'recipient') (2008, p. 159). Previous research has applied the REM framework to relational event sequences consisting of radio communications (Butts 2008), email communications (Quintane et al. 2013), and classroom interactions (DuBois et al. 2013). While Butts' framework was proposed for one-mode data (for instance, events linking trucks to other trucks), we follow Quintane and colleagues (2014) and apply the REM framework to two-mode data (events linking trucks to locations). A relational event in our context is thus a choice 'sent' from a truck to a location. Each event is of the form $a = (i, j, t)$, where *i* is the truck, *j* is the location, and *t* is the time at which the event occurs. The framework assumes that each event is independent of all other events but conditional on the sequence of events that have occurred in the past. This conditional independence assumption implies that ''past history creates the context for present (inter)action, forming differential propensities for relational events to occur'' (Butts, 2008, p. 160).

To model the probability of the sequence of events, we specify the following model:

$$p(A|\beta, s) = \prod_{m=1}^{M} \frac{\exp\,[\beta' s(t_m, i_m, j_m, A_{t_m})]}{\sum_{(i,j)\in\Omega} \exp\,[\beta' s(t_m, i, j, A_{t_m})]}$$

where β is a vector of model parameters; $s(t, i, j, A_t)$ is a vector of statistics pertaining to the truck location pair (i, j); $s(t, i, j, A_t)$ is a function of A_t, the sequence of all actions extending from time 0 up until time *t*; M is the number of events in the sequence; and Ω_m represents a set of six events consisting of the case that occurred at time *m* and 5 controls, drawn randomly from the set R_m of all potential events that could have occurred as the m_{th} action.

A relational event model can be represented as a conditional multinomial logistic regression (Butts 2008). Applying the REM framework to our context, we consider the gourmet food truck market as a time-ordered sequence of location choices made over the one year observation period. We focus on the sequence of location choices and not the precise time at which those choices occur. For each time step in the sequence, we define a set of possible trucks and the locations they may have chosen. We consider a truck as active at the time when they made their first location choice. If there are 49 trucks active in the market and 941 possible locations, there are 49(941) possible pairs of trucks and locations. Fitting the REM amounts to estimating across all sets a conditional multinomial logit model for the probability that of each set consisting of a truck-location pair that occurred and all possible truck-location pairs, it is indeed the observed truck-location pair that occurs. Figure 6 provides an overview of our data construction.

<Insert Figure 6 Here>

The probability of each possible truck-location pair within the set is conditional on statistics computed from the prior sequence of truck-location pairs. Statistics are scaled across all values for observed and potential pairs, based on calculating a proportion of previous pairs, rather than a raw count. For instance, the statistic for *Inertia* is the number of times a truck has chosen a particular location out of the total number of choices made by that truck. It can be interpreted as the extent that truck *i* focuses its vending at location *j*.

The main innovation in our model is that unlike standard entry/exit or contagion models, we do not need to aggregate behavior into time periods, so we do not lose information in this way. As we have information about the sequencing of events, rather than time panels, we can avoid the standard problems of non-independence of observations that affect the probability of an event happening conditional on covariates that include prior states of the system. Imposing sequential dependence in this way avoids more complex simultaneous structures used in models with concurrent relationships. Additionally, REM models can also can handle changes in the set of senders and recipients –as in a new market, where firms enter over time.

5.2 Case-Control Design

One drawback of the REM framework is that is it computationally demanding. Each set can have up to 48,000 possible truck-location pairs and we observe 5,391 location choices and thus 5,391 sets. Preparing the database involves coding a large set of covariates. Many of these, such as *Inertia*, vary over time. Our full database is a 27 GB file with approximately 150 million observations. To reduce computational time, we use a case-control design in estimating our model. Rather than using the full set of all possible truck-location pairs, we randomly select five controls for each truck-location pair that occurs. This reduces our database from 150 million observations to 32,346. As demonstrated by Hu and Van den Bulte (2014), adjusting a conditional multinomial logit model with a case-control design improves computation time while maintaining the precision of the estimates.

6. Covariates

6.1 Contagion Variables

We model social contagion as the effect of exposure to others' prior location choices. One of the aims of our research is to untangle the source of contagion, so we distinguish five conduits through which firms may be influenced:

Contagion from Informational Influence reflects the tendency for truck *i* to choose location *j* as a function of the proportion of times *j* has been chosen in the past out of the total number of location choices made by all truck(s) *l*.

Contagion from Immediate Colleagues reflects the tendency for truck *i* to visit location *j* as a function of the proportion of times *i*'s commissary neighbor(s) *l* have chosen *j* in the past out of the total number of location choices made by all neighbor(s) *l*.

Contagion from Market Pioneer reflects the tendency for truck *i* to visit location *j* as a function of the proportion of times the market pioneer *l* has chosen *j* in the past out of the total number of location choices made by market pioneer *l*.

Contagion from Direct Competitors reflects the tendency for truck *i* to visit location *j* as a function of the proportion of times *i*'s direct competitor(s) *l* have chosen *j* in the past out of the total number of times *j* has been chosen.

Contagion from Agglomeration reflects the tendency for truck *i* to choose location *j* as a function of the proportion of times *j* has been chosen earlier that day out of all location choices made so far that day by all truck(s) *l*.

6.2 Location Choice and Susceptibility to Contagion

Prior experience at a location is likely to moderate a truck's susceptibility to contagion from peers. *First Visit* is a dummy variable taking the value 1 if it is a truck's first visit to a location and 0 if it a repeated location visit. We also control for the tendency for owners to maintain their past patterns of location choice over time rather than alter these patterns in response to information gathered from peers. *Inertia* reflects the tendency for truck *i* to visit location *j* as a function of the extent to which *i* has visited location *j* in the past.

6.3 Control Variables

We control for location, truck, and truck-location characteristics that might be associated with location choice. *Los Angeles* is a dummy variable indicating whether the location is in Los Angeles county. *Median Income* captures the median household income of the zip code containing the location. *Population Density* captures the population density per square mile of the zip code containing the location. *Restaurant Density* captures the number of brick-and-mortar restaurants within a half-mile radius of the location. *New Location* is a dummy variable taking the value 1 if the location has not previously been chosen by any truck. *Regulations* is a dummy variable with the value 1 if the location is within one of the 12 cities and 2 counties with a high level of food truck regulations.

Follower Firm is a dummy variable with a 0 if a firm is Kogi BBQ, 1 otherwise. *Prior Activity* controls for the prior activity of the truck and is also a proxy measure for an owner's experience in the market. It is calculated as the number of prior location choices made by the truck as a proportion of all choices made by all trucks in the market. We also include 21 product category dummies.

Distance from Commissary is the distance, in miles, from the truck's commissary to a location. *Distance from Last Location* is the distance, in miles, from the last location chosen by the truck to a location.

6.4 Descriptive Statistics

Descriptive statistics are reported in Table 2.

<Insert Table 2 Here>

7. Results

Table 3 presents maximum likelihood estimates for three models. Model 1 includes only the controls, model 2 adds the contagion variables, and model 3 explores whether social contagion is moderated by a truck's prior experience at a location by interacting each of the contagion variables with the dummy variable *First Visit*. With the exception of the dummy variables, all covariates have been mean-centered and scaled across all values to make their effects more comparable across model specifications (Quintane et al. 2014). Goodness of fit is reported using the residual deviance measure, which is -2 times the log likelihood ratio (Butts 2008). We fit all models using *clogit* from the Survival package in R.

7.1 Source of Contagion

We first compare our model of social contagion with a model where there is no social contagion. In Model 1, we estimate location choice as a function of market attributes, truck attributes, and the distance to the location from the truck's commissary and last visited location. Model 2 adds contagion variables, the inertia measure, and a dummy variable, *First Visit*, for a truck's first visit to a location. We find that the model incorporating social contagion does significantly better in explaining observed behavior (Δ -2LL = 6,715.54, $p < .01$), providing evidence that location choice is driven by contagion. The negative effect of *First Visit* indicates that trucks are more likely to repeat locations rather than choose a location where they have no previous experience. The positive effect on *Inertia* indicates that the more a truck has focused their visits on a location in the past, the higher the probability that this truck will choose the same location again. Effect sizes can be interpreted similarly to a logistic regression as parameter estimates can be exponentiated to yield odds ratios. For instance, a parameter estimate of -3.58

for *First Visit* indicates that there is a 97.2% (exp(-3.58) = .028) decrease in the likelihood of a truck visiting a location for the first time over a location it has visited before.

Turning now to the five contagion variables in Model 2, the positive effect of *Informational Influence* indicates that popular locations are more likely to receive another visit, a self-reinforcing effect of contagion. The larger parameter, when compared to the size of the other contagion parameter estimates, indicates that *Informational Influence* is the strongest contagion effect. Contagion originating from a truck's *Colleagues* at their commissary and the *Market Pioneer* are both non-significant. Contagion originating from *Agglomeration* via other trucks choosing a location earlier the same day has a positive effect on the tendency for a truck to choose a location. Contagion from *Direct Competitors* has a negative effect, indicating a tendency for trucks to avoid locations visited by their direct competitors.

7.2 Initial Location Choice versus Repeat Location Choice

Model 3 extends the analysis by assessing whether susceptibility to contagion is moderated by a truck's previous experience at a location. Each of the contagion effects is allowed to vary as a function of *First Visit*. This further improves model fit (Δ -2LL = 52.52, $p < .01$). There is an interesting pattern in the findings. *Informational Influence* as well as contagion from *Colleagues* and *Agglomeration* each positively moderate the likelihood of a truck trying a location for the first time. However, the activity of the *Market Pioneer* at the location negatively moderates the likelihood of a truck visiting the location for the first time. This pattern is consistent with the notion that contagion via *Informational Influence*, *Colleagues*, and *Agglomeration* each reduce the perceived ambiguity and risk associated with trying a location for the first time, though through different means. The negative influence of the *Market Pioneer* effect suggests that Kogi BBQ's preference for a location dissuades follower firms from trying that location for the first time. Contagion from *Direct Competitors* is not moderated by a truck's previous experience at a location: there is no significant interaction between *Direct Competitor* contagion and *First Visit*.

Turning now to the main effects, we find that when repeating a visit to a location, *Informational Influence* has a positive effect, though it is smaller than when trying a location for the first time. Contagion from *Direct Competitors* has a negative effect on repeating a visit to a previous location. Contrary to our prediction in H2, contagion from *Colleagues* has a negative effect on repeating a visit to a location, rather than the positive effect predicted. This pattern of results indicates that a truck has a tendency to try new locations that are preferred by their neighbors at the commissary but then avoid repeating visits to locations that are preferred by their neighbors at the commissary. So when trucks are uncertain about a location, they are susceptible to normative influence from their colleagues, but when they have experience at a location, they are more likely to deviate from their colleagues' behavior. Contagion from the *Market Pioneer*, which had a negative effect on trying a location for the first time, has a positive effect on repeating a visit to a location. This finding is consistent with the notion that the market pioneer prevents weaker competitors from accessing the best locations in the market (H4). We find no significant main effect for *Agglomeration* on repeating a visit to a location. This suggests that contagion through *Agglomeration* increases a firm's tendency to visit a new location, but has no effect when a firm has prior experience at a location.

Thus we find full support for H1 and H4 and partial support for H2, H3, and H5.

7.3 Other Variables

Location characteristics included as control variables do not show consistent coefficients across the location choice and location choice versus repeat columns in Table 3. Locations in Los

Angeles County and locations in zip codes with higher median incomes have an increased likelihood of attracting trucks. There is no consistent effect for population density, restaurant density, distance to the location, or regulations. Surprisingly, when the coefficient for regulations is significant, it has a positive effect, indicating that locations in cities with more food truck regulations are associated with more visits.

8. Discussion

We investigated the presence and nature of contagion in mobile food trucks' choice of locations. There are three novel findings. First, we find evidence of contagion not only in location choice but also in repeat location choice. Consistent with our assumptions that contagion in location choice is driven primarily by uncertainty, we find that contagion has a stronger effect on a truck trying a location for the first time rather than a truck repeating a visit to a location.

Second, who is most influential varies across the stages. The market pioneer's choices have a negative influence on trying a location. In contrast, proximate colleagues and agglomerating colleagues have a positive influence on trying a location. For repeat visits, the market pioneer has a positive influence while proximate colleagues have a negative influence. The pattern of results is consistent with proximate colleagues and agglomeration reducing risk in trying a location and competition limiting entry.

Third, we find that in contrast to much coverage in the media that has focused on the impact of regulations and conflict between food trucks and brick-and-mortar restaurants, the location choices of trucks' peers are more important than the attributes of the locations in driving food trucks' decisions to try or revisit a location. After adding in the choices' of trucks' peers in models 2 and 3, many of the location controls become non-significant.

Our findings make a significant contribution to the literature on market entry. We complement recent studies showing the role of uncertainty in models of learning and social contagion among firms making location decisions (Shen and Xiao 2014; Toivanan and Waterson 2005; Yang 2013). Specifically, we demonstrate that this effect exists not only when choosing a location, but also in markets where firms can relocate and make additional location choices.

These findings about the role of prior experience in location choice behavior complement and extend recent work on the role of social contagion in new product trial and repeat behavior (Iyengar et al. 2015). Furthermore, we bridge the literatures on social contagion in market entry and social contagion in consumer adoption by showing that mechanisms that operate in consumer contagion (Iyengar and Van den Bulte 2001) also play a role in social contagion among firms.

In introducing the relational event framework, our study offers social contagion researchers in both the consumer contagion and firm contagion arenas a new approach for understanding how and why contagion is at work (Aral 2011; Godes 2011). Exploiting the timing of adoption decisions, rather than using panel data, provides researchers with a flexible toolkit for distinguishing mechanisms and exploring dynamic social processes on networks.

Our study will also be of interest to researchers in the related area of competitive dynamics. Our finding that on average, firms repeat only about 40% of their location choices suggests that many firms in markets without costless relocation are competing from sub-optimal locations. While Hotelling (1929) allows for relocation, much marketing research since has assumed that relocating a retail location or a product's positioning is too costly and thus irrevocable. However, many firms now sell products and services that can be repositioned quickly. Not only firms selling products and services online, but also fast-fashion retailers like

H&M and Forever 21, whose sophisticated supply chains allow them to bring new products to market in a few weeks or months. We encourage further research in this area.

As our study was limited to a unique market—gourmet food trucks in Southern California—corroboration in other settings would be useful. Many firms now offer products and services on demand, delivered through a smartphone application to a user's location. Future research might consider location strategies in a context such as the strategies used by Uber drivers. The cost of gasoline, Uber's "surge pricing," the ability for drivers to observe each other's locations in real-time, and the uncertainty around the passenger's destination prior to pick up makes this market a complex setting where relocation is even more frequent and contagion likely plays a significant role.

Future research might also consider the impact of shifting regulations on food truck location choices in more detail. This market went through a legitimation process (Humphreys 2010), with many changes to consumer attitudes and local laws. We want to point out that there might be other explanations that can rationalize our counterintuitive finding that trucks have a slight preference for cities with food truck restrictions and our analysis does not rule out these alternative explanations. First, we use a dummy variable for *Regulations* and thus consider all cities with restrictions as the same. Second, by aggregating locations at 100 meters, we cannot observe in our data whether trucks are parking on public property, where they would be subject to regulations, or private property, where they might experience less enforcement. Third, there is the possibility of selection bias, as we observe only locations chosen at least once. Finally, media coverage from the 2008-2010 time period suggests that some owners chose to flaunt local ordinances, considering parking tickets as a cost of doing business (Pou 2010).

Our findings are also of interest to practitioners. An important practical implication of our research is the degree to which firm behavior is driven by peers. While the media coverage of the gourmet food truck market has focused largely on their relationship with brick-and-mortar retailers, we find that the location choice strategies are shaped less by the attributes of the locations, such as the presence of brick-and-mortar restaurants—and more by the activity of other trucks at those locations. A small number of early choices can be critical in determining the future spatial structure of a market, especially in categories where firms can easily observe each other. Early entrants are likely to be pivotal influencers. Many managers are now aware of the importance of targeting consumers with WOM marketing campaigns. Our results suggest that WOM marketing strategies should take into account whether and how firms can use social media to learn from others.

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Figure 1 Panel A: Distribution of locations chosen by Kogi BBQ at one year.

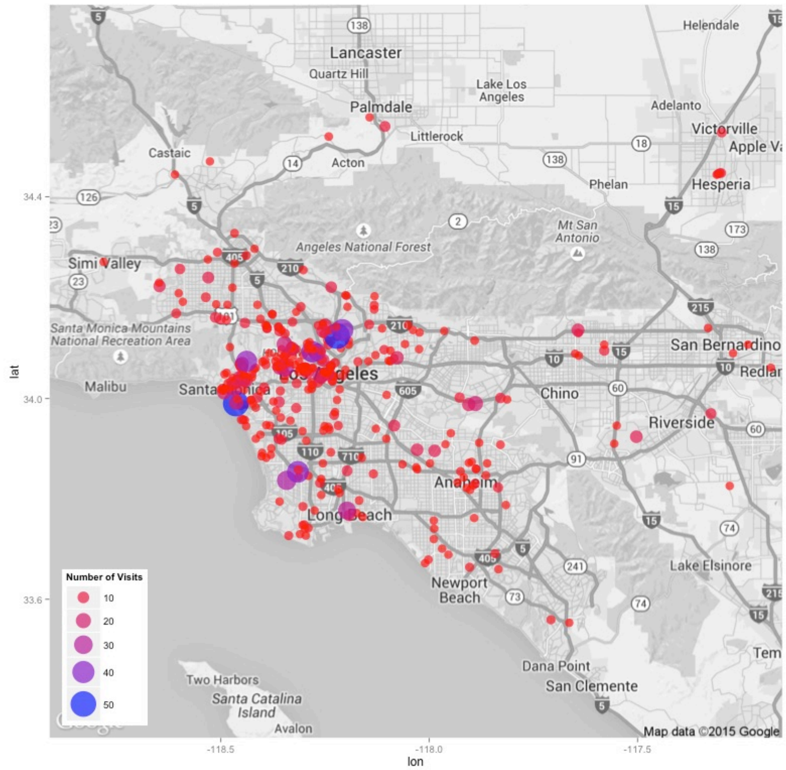


Figure 1 Panel B: Distribution of locations chosen by Calbi BBQ at one year.

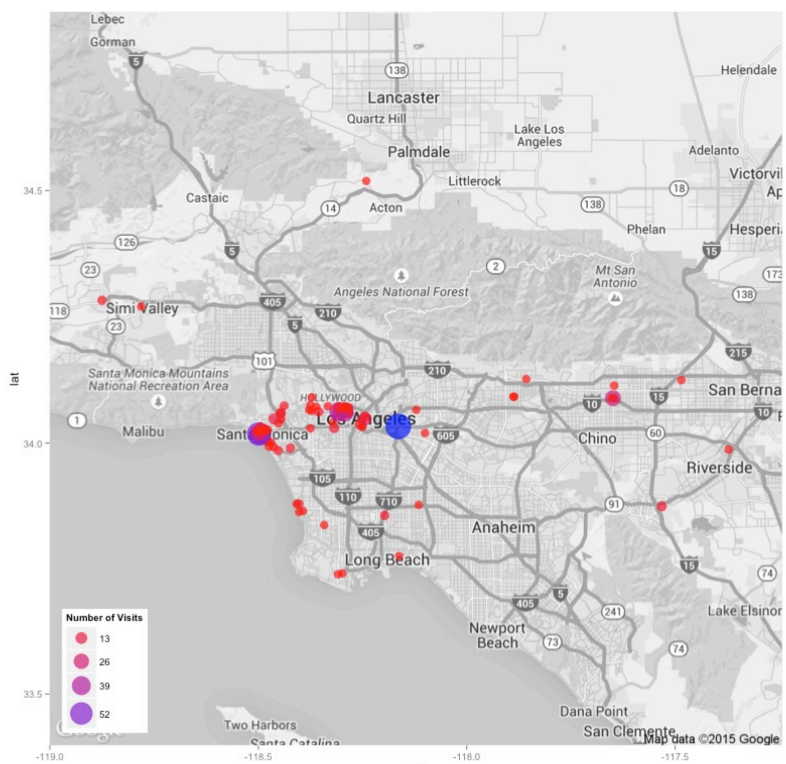
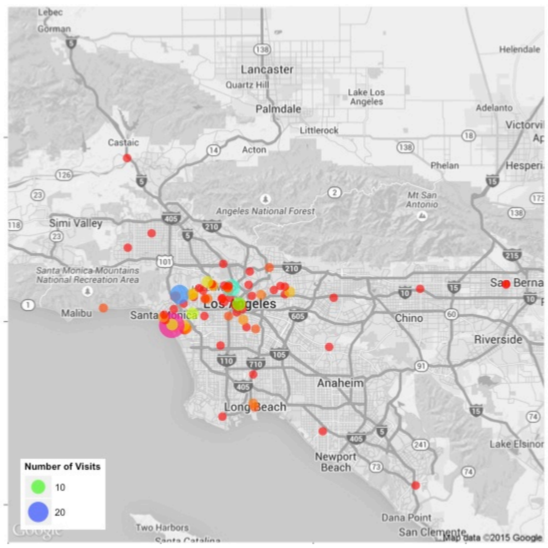
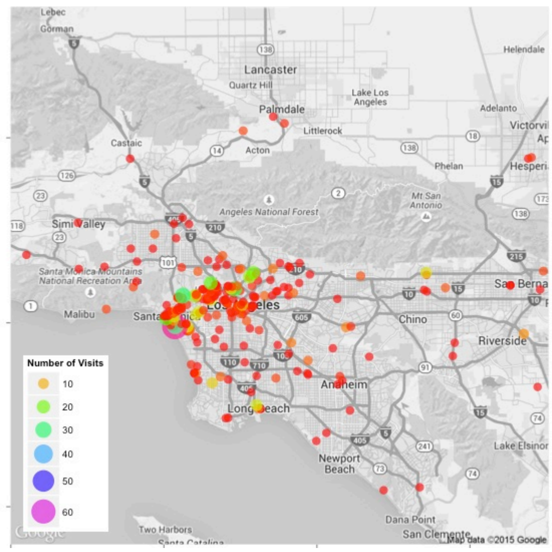


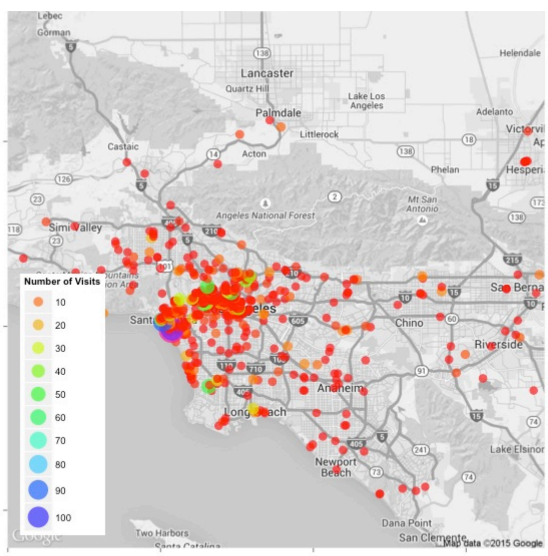
Figure 2: Spatio-temporal development of the gourmet food truck market.



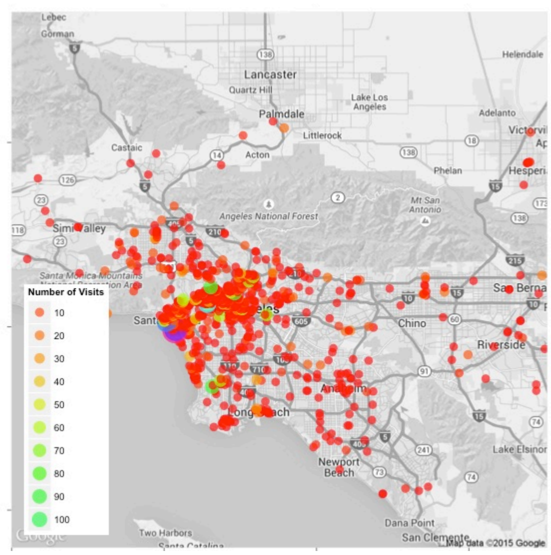
(a) February 2009



(b) May 2009



(c) August 2009



(d) November 2009

Figure 3, Panel A: Increase in number of trucks and locations over time.

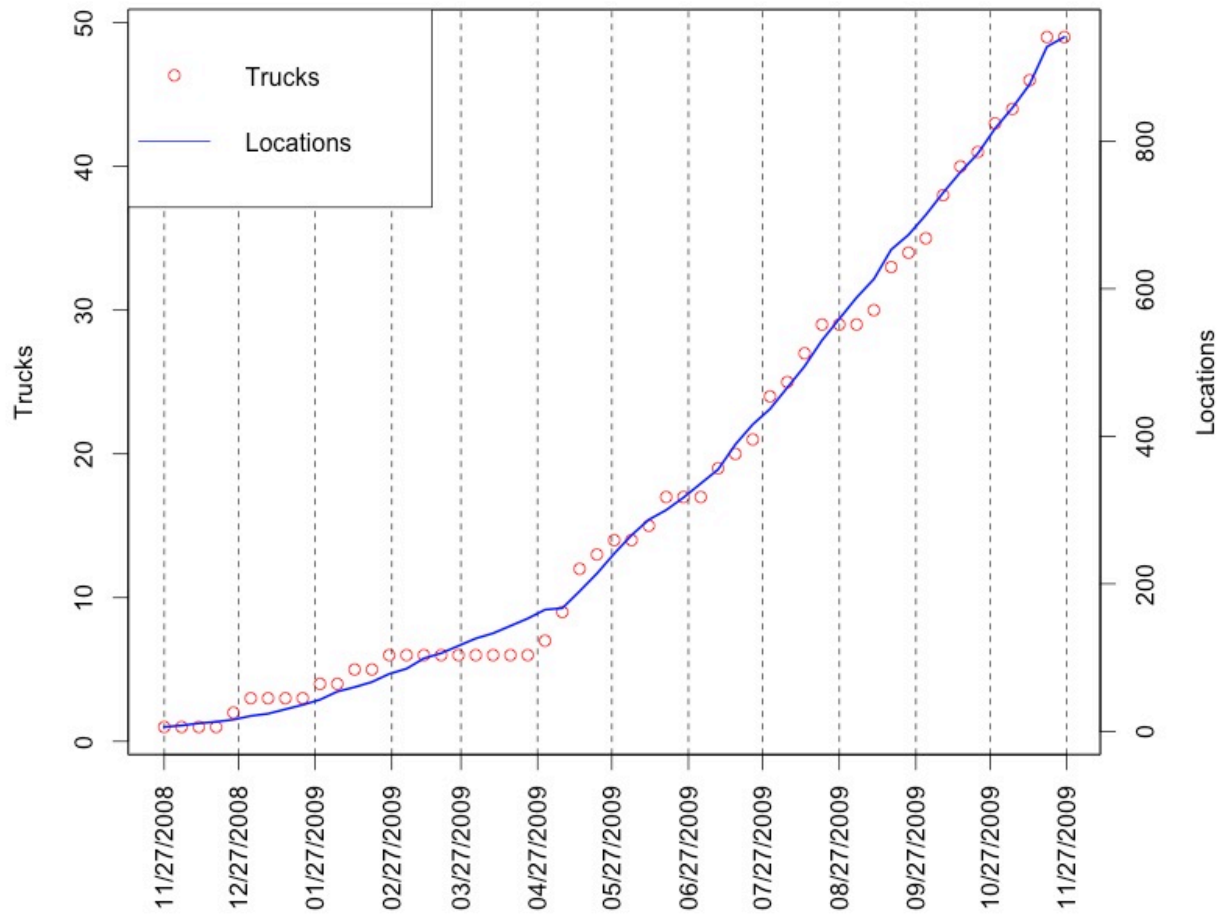


Figure 3, Panel B: Number of active trucks per day (with weekly moving average).

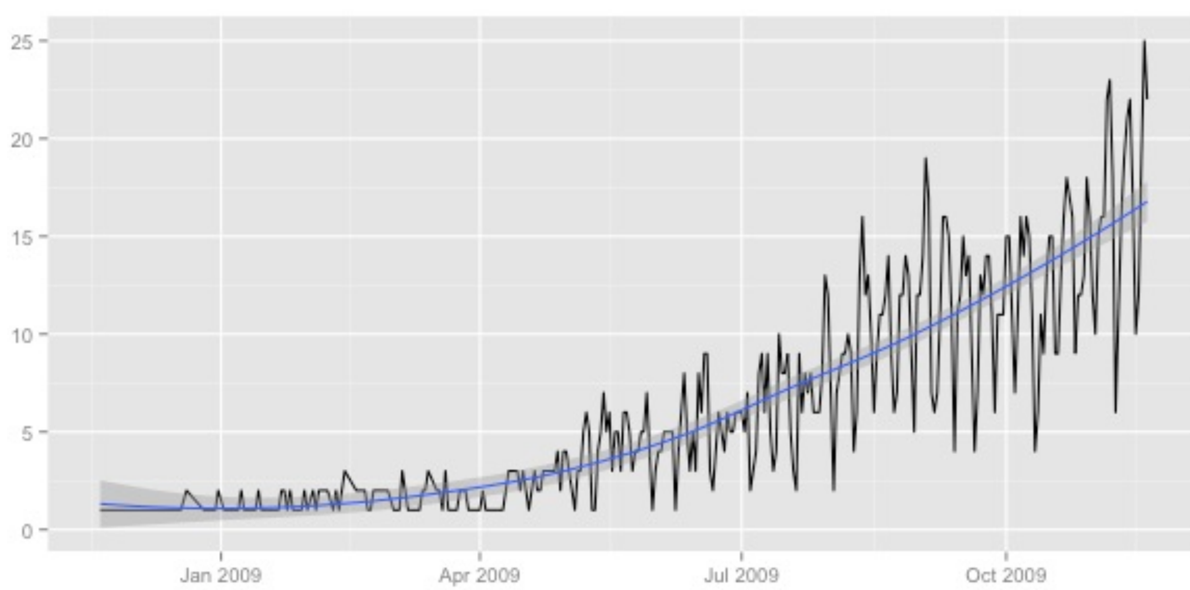


Figure 4: Histogram of location visits: number of locations and number repeated.

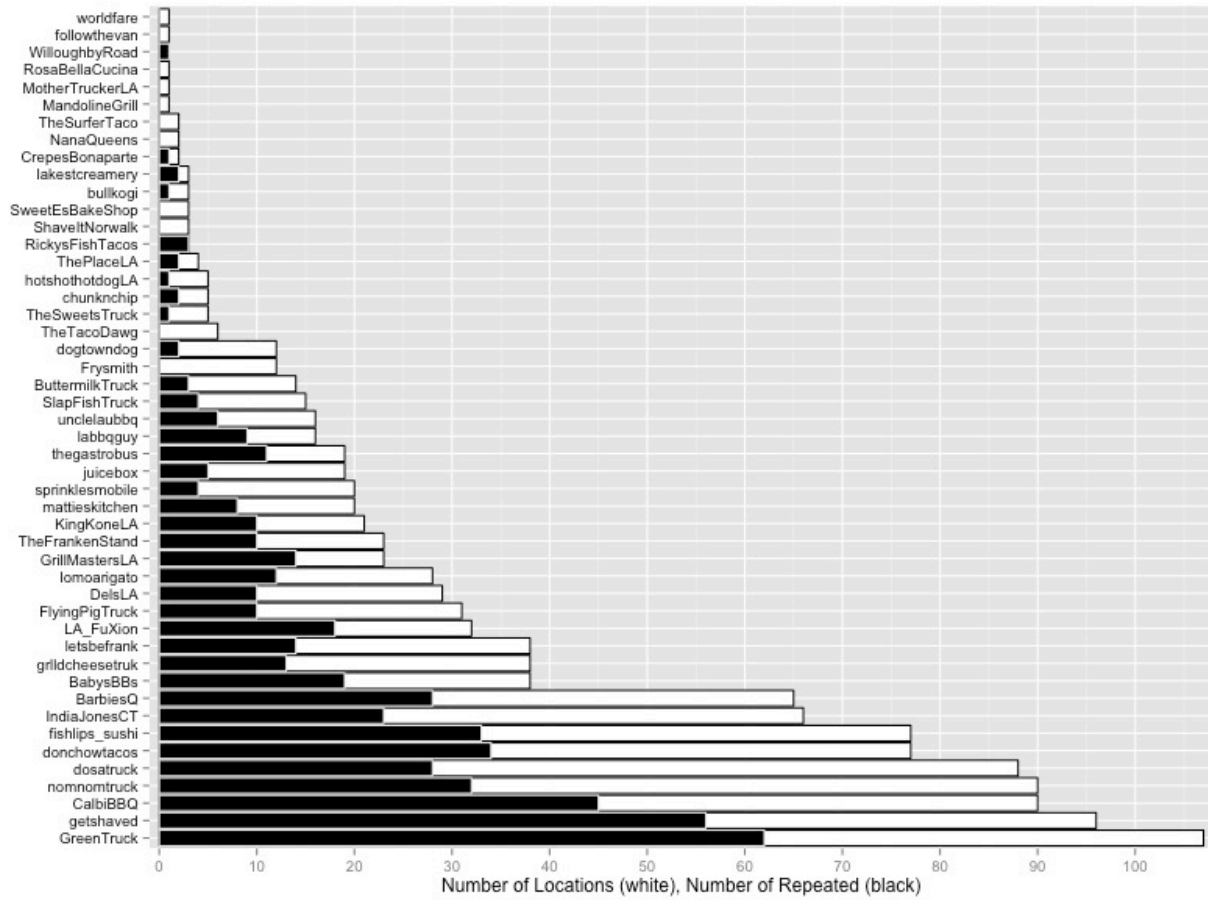


Figure 5: Example of our data setup.

Date:Time	Truck	Location
2008-11-20:18:04:43	Kogi BBQ	34.147,-118.144
2008-11-21:18:08:06	Kogi BBQ	34.108,-118.347
2008-11-22:00:28:11	Kogi BBQ	34.012,-118.492
2008-11-22:08:18:20	Kogi BBQ	34.098,-118.329
2008-11-23:00:14:13	Kogi BBQ	34.096,-118.329

Figure 6: Example of our data construction**.**

Time	Truck	Location	Inertia
1	A	1	0
1	A	2	0
1	B	1	0
1	B	2	0
2	A	1	1
2	A	2	0
2	B	1	0
2	B	2	0
3	A	1	1
3	A	2	0
3	B	1	0
3	B	2	0
4	A	1	.66
4	A	2	.33
4	B	1	0
4	B	2	0

Consider a market made up of two trucks (A & B) and two locations (1 & 2). At each time step, a truck picks a location. We observe a sequence of four location choices (shaded in gray above): A-1, A-1, A-2, A-1. For each time step, we define the set of possible trucks and locations. With two trucks and two locations, there are four possible pairs at each time step.

We compute a statistic—*Inertia*—that captures the tendency for trucks to prefer some locations over others. It is calculated here as the proportion of times that a truck chooses a location out of all the choices made by the truck in the past. No choices have been made prior to time 1, so at time 1, Inertia is 0 for all possible pairs. At time 2, truck A has chosen location 1 for 100% of its choices, so Inertia is 1 for the A-1 pair and 0 for all other possible pairs.

Table 1: Overview of hypotheses.

Hypothesis	Proposed Relationship: First Visit	Proposed Relationship: Repeat Visit
H1: Location choice behavior is affected by social contagion that originates from observing others	+	+
H2: Location choice behavior is affected by social contagion that originates from proximate peers	+	-
H3: Location choice behavior is affected by social contagion that originates from direct competitors	-	-
H4: Location choice behavior is affected by social contagion that originates from the market pioneer	-	+
H5: Location choice behavior is affected by social contagion that originates from agglomeration	+	+

Table 2: Descriptive statistics of the control covariates included in the model.

Variable	Measure	Mean	Min	Max
Los Angeles	1 = location in LA county; otherwise 0	88.7%	0	1
Median Income	The median household income in the zip code containing the location	$59,977	$9,219	$153,621
Population Density	The population density per square mile in the zip code containing the location	10,928.3	2.47	50778.8
Restaurant Density	Number of brick-and-mortar restaurants in a .5 mile radius around the location	66.1	0	438
Regulations	1 = location is in a city or county with stringent food truck regulations; otherwise 0	10.5%	0	1
New Location	1 = no truck has previously visited the location; otherwise 0	37.9%	0	1
Follower Firm	1 = truck is a firm that entered the market after Kogi BBQ, 0 = Kogi BBQ	90.3%	0	1
Prior Activity	Number of prior location choices made by the truck as a fraction of all prior location choices made by all trucks	-	0	1
Distance from Commissary	Geographic distance from the food truck's commissary to the location, in miles	17.7 miles	.03	93.8
Distance from Last Location	Geographic distance from the last location used by the food truck to the location, in miles	17.2 miles	0	116.3

Table 3: Model estimates. Rightmost column indicates which hypothesis predicts positive/negative values for which parameter.

	Controls (1)	Contagion (2)	Contagion x First Visit (3)	*Prediction*
Variables of focal interest				
First Visit		-3.58*** (0.09)	-3.69*** (0.10)	
Inertia		0.15*** (0.04)	0.18*** (0.04)	
Contagion from Informational Influence		0.79*** (0.05)	0.65*** (0.08)	H1 (+)
Contagion from Colleagues		0.03 (0.02)	-0.09** (0.03)	H2 (-)
Contagion from Direct Competitors		-0.13*** (0.03)	-0.23* (0.10)	H3 (-)
Contagion from Market Pioneer		-0.03 (0.04)	0.28** (0.10)	H4 (+)
Contagion from Agglomeration		0.10** (0.03)	-0.01 (0.03)	H5 (+)
Contagion from Informational Influence x First Visit			0.21* (0.10)	H1 (+)
Contagion from Colleagues x First Visit			0.14*** (0.04)	H2 (+)
Contagion from Direct Competitors x First Visit			0.11 (0.11)	H3 (-)
Contagion from Market Pioneer x First Visit			-0.34** (0.11)	H4 (-)
Contagion from Agglomeration x First Visit			0.18*** (0.04)	H5 (+)
Control variables				
Los Angeles	0.73*** (0.09)	0.28* (0.13)	0.25* (0.13)	
Median Income	0.16*** (0.02)	0.06* (0.03)	0.066* (0.03)	
Population Density	-0.02 (0.02)	-0.03 (0.03)	-0.02 (0.03)	
Restaurant Density	0.06** (0.02)	0.03 (0.03)	0.03 (0.03)	
Regulations	0.18** (0.06)	0.18* (0.09)	0.18. (0.09)	
New Location	-1.41*** (0.05)	0.77*** (0.08)	0.80*** (0.08)	
Follower Firm	0.33* (0.14)	0.50* (0.20)	0.48* (0.20)	
Prior Activity	0.67*** (0.06)	0.42*** (0.07)	0.42*** (0.07)	
Distance from Commissary	-0.07* (0.03)	-0.07. (0.04)	-0.07. (0.04)	
Distance from Last Location	-0.12*** (0.03)	-0.07. (0.04)	-0.07. (0.04)	
Null Deviance		19,318.8		
Residual Deviance (-2LL)	13,478.98	6,763.44	6,710.92	

Note: The numbers in parentheses are the standard errors for the parameters.
* indicates p <.05, ** indicates p <.01, *** indicates p <.001, All models include 21 product category dummies.

ESSAY 3:

Identifying Strategies for the Evolution of Cooperation in Social Networks

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Introduction

The 'Survival of the Fittest' is a common expression in both biology and business. Evolution and economics would seem to favor selfish behavior. Yet decades of research have demonstrated the benefits of cooperation in groups of social animals or competing firms. While there is strong evidence for the benefits of cooperation, there is conflicting evidence for its maintenance; when individuals cooperate for shared benefits, there is often a larger benefit to be gained through defecting and cheating the cooperators. If morality, religion, and lawyers are recent human inventions, then animals and early humans must have utilized some other system to control cheating and make social life a little less nasty, a little less brutish.

Evolutionary biology suggests that behavior is guided by simple strategies or decision rules which emerge out of social interactions and bring order and cooperation to social groups (De Waal 1996; Axelrod and Hamilton 1981). In this literature, the problem of cooperation is typically formulated using a game-theoretic model, such as Prisoner's Dilemma, in which two individuals simultaneously choose between cooperation and defection. Typically, each player is hardcoded with a particular strategy that determines their decision to cooperate or defect on the next move. Using this approach, researchers across evolutionary biology and the social sciences have identified a number of strategies which can produce cooperation. The most well-known strategy is direct reciprocity (Axelrod and Hamilton 1981; Trivers 1971): individuals provide assistance to others at a cost that is offset by benefits received in return. A number of alternatives to direct reciprocity have been proposed: network reciprocity (Ohtsuki et al. 2006) operates by allowing cooperators to interact more with other cooperators, thus avoiding defectors; the theories of indirect reciprocity (Nowak and Sigmund 1998) and costly signaling (Zahavi 1977) are based on the ability of cooperators to build a reputation; altruistic punishment (Fehr and

Gächter 2002) allows cooperators to punish defectors; generalized reciprocity (Hamilton and Taborsky 2005; Rutte and Taborsky 2007) leads to cooperation through a “Pay It Forward” process (Gray et al. 2014), where prior receipt of help increases the propensity to help others.

While the existence of many of these strategies has been confirmed with ethnographic and experimental evidence, it remains unclear to what extent they generalize to real-world social groups with more complex interactions. Evidence suggests that strategies developed for pairwise or small-scale interactions in stable groups, such as direct reciprocity, do not operate as well in large, dynamic group interactions (Boyd and Richerson 1988). Research thus far has tended to examine each strategy in isolation. Although we have evidence that they coexist in nature, little research has explored how they act in concert (Clutton-Brock 2009; Rand and Nowak 2013). This suggests a need for integrated models of cooperative behavior.

Here, we propose a new approach to the longstanding puzzle of cooperation. We introduce a framework for modeling cooperation within social settings that builds on recently developed dynamic network models for sequence analysis (Butts 2008) and previous work using Prisoner’s Dilemma games. In the game theoretic tradition, a researcher specifies a strategy or collection of strategies for the players to follow, sets the conditions and assumptions of the game, and then observes how much cooperation results when the sequence of moves in the game is over. We flip this approach. We start with an observed sequence of individual cooperative or selfish actions. We then use patterns in the sequence to infer the strategies that produced the action. This framework supports likelihood-based inference, allowing the researcher to estimate the relative roles of potential strategies as well as select among competing models. It can be implemented simply. It accommodates any time sequence of human or animal behavioral data.

We believe this approach creates new opportunities for the field to move from simulating how cooperation can evolve to the richer project of measuring how it does evolve.

To test our framework, we model the evolution of cooperation over the first two years of the gourmet food truck market in Southern California. Gourmet food trucks are mobile restaurants that use Twitter to announce their locations to their customers. This setting is a unique venue featuring many of the conditions specified by Axelrod (1984) as necessary for the evolution of cooperation. During its early years, the market went through a ‘Wild West’ phase: the low cost of starting a food truck meant an influx of entrepreneurs, experimenting with new types of food, while regulation that could not keep pace (Coolican 2010). The restaurant industry is known for welcoming misfits (Bourdain 2013) and as a one food truck owner explained in an interview, “food trucks get the misfits of the misfits.” We thus have a social group with no central authority, little outside oversight or regulation, a high level of experimentation, and large rewards for self-interested behavior. And out of this soup emerges cooperation: truck owners began cooperating by promoting each other’s trucks on Twitter. For instance: @getshaved: “Check it out...@lakidstuff posted a nice little blurb about us and our friends @coolhaus and @sprinklesmobile - http://bit.ly/DLa9D.”

We use two years of Twitter data: consisting of 152,312 Tweets from all 211 food trucks active in the market over the observation period. We find that 53.1% of trucks cooperate and we observe a total of 14,103 promotions exchanged between trucks. Cooperating trucks promote 25.2 other trucks on average.

These data allow us to study cooperation because promoting another truck owner is costly to the sender of the Tweet but beneficial to the receiver. If the receiver of the Twitter mention does not reciprocate the Tweet, they will receive free advertising at the cost of time and potentially lost customers from the sender. Tweets are public and so a truck's current choice to cooperate or defect as well as their historical choices are visible not only to the researcher but also to other trucks in the market. We observe owners asking for mentions and thanking senders when they receive them, confirming that promotions are a valued resource or currency in this group.

In our framework, n individuals form a social group. Interactions in the group unfold in a sequence of t time steps. At each time step in the sequence, any individual can send a cooperative action to any other individual in the group. Consistent with the game theoretic approach, we assume that cooperative actions are independent conditional on the past history of cooperative actions (Butts 2008). We allow individuals to choose to defect instead of cooperate by sending the cooperative action to themselves rather than another member of the group. In our context, when a truck mentions another truck on Twitter, we consider the cooperative action to be the promotion sent from one truck to another. If a truck mentions multiple trucks in the same Tweet, we duplicate the Tweet, so that each truck mentioned is represented as a unique sender-receiver pair (see table S4). When a truck sends a Tweet that only promotes themselves, we consider it a defection. Each time step of the sequence is thus of the form $a = (i, j, t)$, where i is the sender of the action, j is the receiver, and t is the time at which the action occurs.

The key innovation of our approach is that we can distinguish between the effects of various strategies, such as direct reciprocity and generalized reciprocity, and directly estimate the contribution of each strategy to the entire sequence of interactions. We do so by incorporating "cooperation shifts" in our modeling setup–effects similar to the "participation shifts" proposed by Gibson (2003; 2005) and incorporated by Butts (2008) into the relational event framework. Participation shifts capture transitions in who is speaking and who is being addressed and are a basic means of capturing the effect of conversational norms, such as a speaker claiming the floor, on a single-channel communication sequence such as interaction on one radio channel (Butts 2008) or in a small group meeting (Gibson 2005). While trucks can see each others' messages on Twitter, Twitter is not a single channel where each Tweet momentarily holds the floor. We thus formulate cooperation shifts as local effects, rather than global: each time an individual acts in the sequence, we identify their most recent appearance in the sequence as either the sender or receiver of an action. For each of these two time step-long sequences in our data, we categorize the possible ways a social interaction can unfold. For example, where *A*, *B*, and *Y* are distinct trucks, the cooperation shift *AB-BA* represents direct reciprocity, where truck *A* promotes truck *B* and then at *B*'s next action in the sequence, *B* promotes *A*. Similarly, the cooperation shift *AB-BY* denotes a generalized reciprocity pattern, where *A* promotes *B* is followed by *B* promoting another truck, *Y*. In Table 1, we link these patterns, such as *AB-BA*, to common strategies from evolutionary game theory. (Table 1). Fig. 1 provides an illustration of our modeling setup (see Supplementary Information section 1 for further details).

This approach is related to a number of recent studies using a relational events framework (Butts 2008; Kitts et al. ; Quintane et al. 2014). However, we extend existing techniques in three ways: 1) allowing for self-ties, as in the choice to send a cooperative action to oneself; 2) our implementation of cooperation shifts, and 3) a case-control design, which significantly reduces computation time while maintaining the precision of our estimates (Hu and Van den Bulte 2014). Our work is also related to a number of recent studies exploring the effect of networks and population structure on cooperation (Fowler and Christakis 2010; Rand et al. 2011; Van Veelen et al. 2012; Wang et al. 2012). Our approach is a departure from these studies in several ways. By using observational data rather than experiments, we impose fewer constraints on behavior;

trucks in our study are free to change partners at any time, enter or exit the social group, and vary their level of activity. Unlike the symmetric interactions in Prisoner's Dilemma games, Tweets are asymmetric: the receiver of the Tweet is free to ignore the relationship. Our use of directed ties is thus a better model for real-world cooperative actions, such as gifts or requests for help, which are sometimes never acknowledged by the receipt. This provides a more accurate model of interactions in a social group.

To model the probability of each potential action being the next to occur in the sequence, given the previous history of actions, we specify the following model:

$$p(A|\beta, s) = \prod_{m=1}^{M} \frac{\exp\left[\beta' s\left(t_m, i_m, j_m, A_{t_m}\right)\right]}{\sum_{(i,j)\in\Omega} \exp\left[\beta' s\left(t_m, i, j, A_{t_m}\right)\right]}$$

where each action is of the form $a = (i, j, t)$, where *i* is the sender of the action, *j* is the receiver, and *t* is the time at which the action occurs; β is a vector of model parameters; $s(t, i, j, A_t)$ is a vector of statistics pertaining to the dyad (i, j); $s(t, i, j, A_t)$ is a function of A_t, the sequence of all actions extending from time 0 up until time *t*; M is the number of actions in the sequence; and Ω_m represents a set of six actions consisting of the case that occurred at time *m* and 5 controls, drawn randomly from the set R_m of all potential actions that could have occurred as the m_{th} action.

Our model can be implemented as a conditional multinomial logistic regression (Butts 2008). We use the past history of interaction—the sender of cooperation-receiver of cooperation pairs that occurred in earlier time steps—to predict the next sender-receiver pair in the sequence, relative to sender-receiver pairs that could have occurred. In other words, we estimate across all case-control sets a conditional multinomial logit model for the probability that of the each sextet consisting of an action that occurred and its five controls, that it is indeed the case that occurs.

We include controls for several attributes that may provide alternative explanations for the tendency of a truck to send or receive promotions. *Activity* controls for a truck's overall tendency to Tweet, as that may affect their likelihood to send or receive a promotion. It is calculated as the number of prior actions in which the truck is the sender as a proportion of all prior actions in the sequence. The variable *Direct Competitor* controls for the tendency of a truck not to promote another truck selling the same product. Similarly, the variable *Complement* reflects the intuition that a truck selling a main course item such as tacos may be more likely to promote a dessert truck over a truck selling another main course item. An additional concern is confounding—the tendency for connected individuals to be exposed to the same external stimuli (Shalizi and Thomas 2011). The variable *Shared Commissary* controls for the sender and receiver parking at the same commissary at night. Finally, because we transform a Tweet that promotes multiple trucks into distinct sender-receiver actions in the sequence, we add a control for *Sequential Tweets*.

Results and Discussion

We begin by examining the evolution of cooperation over time. Figure 2, Panel A reports the fraction of trucks cooperating per month and the fraction of Tweets that were cooperative per month. Consistent with recent experiments showing high levels of cooperation when subjects can choose their partners (Rand et al. 2011; Wang et al. 2012), we find that cooperation is maintained at a high level, rather than declining, as in static networks (Suri and Watts 2011; Traulsen et al. 2010). Figure 2, Panel B shows the distribution of trucks by their individual cooperation levels and indicates heterogeneity of behavior: a few trucks had a high level of cooperation (above 50%), about half had no cooperation, and the remainder cooperated in less than 20% of their Tweets.

Figure 3 presents the final state of the cooperation network. By the end of two years, 53.1% of trucks had sent at least one promotion and 67.8% had received at least one. Of the trucks that never promoted another truck, 39.4% received at least one promotion. Thus the network consists of 60 isolated defectors, 39 defectors who received at least one promotion from a cooperator, and a densely connected component of 112 cooperators.

We observe a total of 14,103 promotion ties between 2,009 unique sender-receiver pairs. We find a high level of reciprocation—68.4% of promotions are reciprocated—consistent with theories of direct reciprocity (Axelrod and Hamilton 1981) and a common feature of social networks (Granovetter 1985). Cooperators promote 25.2 different trucks on average (median 22, range: 1:84). Figure 4 shows the frequency of ties that involve two cooperators (CC) or one cooperator and one defector (CD). As defectors do not promote others, there are no links between two defectors (DD).

When a new relationship forms, the tie involves two cooperators 78.4% of the time. Of the 433 pairs where a cooperator promotes a defector: in 21.9% of pairs, the defector then returns the promotion to the cooperator, becoming a cooperator themselves; in 47.3% of pairs, the defector becomes a cooperator when they promote a different truck; in only 30.7% of pairs does the defector remain a defector. When the defector remains a defector after receiving a promotion from a cooperator, 66.9% of the time, the cooperator gives the defector a second chance, repeating the promotion. Rarely (10.2%) does a cooperator promote a defector, then immediately sever ties with the defector for not reciprocating. As a whole, the cooperators retain 96.2% of the promotions they send: only 535 of 14,103 promotions are 'lost' to free-riding defectors who do not convert to cooperation.

Cooperation can evolve when network structure allows for cooperators to cluster (Eshel and Cavalli-Sforza 1982) and this is what we observe in the food truck network: cooperators associate primarily with other cooperators, largely avoiding defectors or converting defectors to cooperators. So while we observe some free-riding, it appears that cooperators are for the most part able to avoid the 'Tragedy of the Commons' (Hardin 1968). These findings are consistent with Wang and colleagues (Wang et al. 2012), who found that clustering resulted primarily from cooperators avoiding defectors, not from severing ties.

While providing some indication of the relative roles of direct reciprocity and altruistic punishment in the food truck cooperation network, these descriptive analysis do not account for the interaction dynamics, nor the wide range of strategies available to each individual. Figure 5 displays the frequency of each cooperation strategy, by month. Next we turn to the results of the model.

Maximum likelihood estimates for our model are presented in Table 2. The parameter estimates represent the influence of a given variable on the probability of each potential promotion sent from *i* to *j* being the next to occur in the sequence, given the previous history of action. *AB-BA*, for instance, estimates the effect of sender *i* having received a promotion from receiver *j* as their last action in the sequence on the tendency for *i* to send to *j* as the next action in the sequence. In separate regression models, each strategy is a significant predictor of the next action to occur in the sequence (see table S2). The parameter estimates can be interpreted similarly to logistic regression as parameter estimates can be exponentiated to yield odds ratios. For example, a parameter estimate of .17 for *Complement* indicates that there is an 18%, exp(.17)

= 1.18, increase in the likelihood of a sender to promote a receiver when the sender and receiver sell complementary products. In line with other studies using a relational events framework, we standardized all variables to make their effects comparable (Quintane et al. 2013; Quintane et al. 2014).

We find the strongest effects for the most selfish strategies. The cooperation shift *AA-AA*, which captures the tendency for a truck to promote themselves twice, has the largest effect of any of the strategies. The second strongest effect is *AB-BB*, which denotes a defection pattern, with B receiving a promotion from A and choosing to promote themselves instead of reciprocating. We find a smaller, but positive effect for *AB-AB*, a forgiving pattern, confirming what we observe in the descriptive analysis: trucks will repeat a promotion, even if it not reciprocated. Similarly, we find a positive effect for *AB-AY*, a cooperative pattern, where A promotes B, does not receive a reciprocation from B, and moves on by promoting Y.

The negative effect of the cooperation shift for altruistic punishment, *AB-AX*, shows that trucks have a lower probability of ending a relationship with a peer who did not reciprocate a promotion. Previous research has generally assumed that punishment supports the evolution of cooperation, as it allows people to punish individuals who do not cooperate (Boyd et al. 2003; Hauert et al. 2007; Fowler 2005). Importantly, this evidence is from anonymous one-shot games, without the possibility for repeated interactions where one can develop a reputation (Dreber et al. 2008; Ohtsuki et al. 2009). Our results collaborate recent findings (Peysakhovich et al. 2014), providing evidence that punishment is not a strategy for the evolution of cooperation (Nowak 2006).

In comparing the three reciprocity strategies, we explore whether direct reciprocity, the most frequent explanation for the evolution of cooperation, is a stronger predictor of future cooperative action than generalized reciprocity or indirect reciprocity. We find that the cooperation shift for generalized reciprocity, *AB-BY*, has a larger effect than both direct reciprocity, *AB-BA* (Wald test, $X^2 = 1536.4$, df = 2), and indirect reciprocity, *AB-YA* (Wald test, $X^2 = 1248.4$, df = 2). Direct reciprocity has a larger effect than indirect reciprocity (Wald test, $X^2 = 814.9$, df = 2).

This finding is consistent with previous research showing that direct reciprocity does not scale well to larger social groups (Boyd and Richardson 1988). One of the limitations of using Prisoner's Dilemma as a metaphor for social interactions is that game theoretic models are constrained to pairwise interactions. However, in real-world interactions, such as food truck Twitter promotions or the distribution of food in foraging societies (Gurven et al. 2002), cooperative actions often involve multiple receivers. We can reverse this finding—resulting in direct reciprocity becoming a stronger effect than generalized reciprocity—by considering an alternative dataset that has no multiple receiver Tweets (tables S3:4).

Conclusion

In this paper, we have introduced a new framework for modeling the relative role of different strategies in supporting the evolution of cooperation. As a context, gourmet food trucks represent a large departure from previous research. Yet at a high level, our results present a chronological picture of the evolution of cooperation that is consistent with prior work. We have demonstrated that many of the strategies identified by theoretical research and verified by laboratory experiments operate similarly in real-world interactions. Our finding that trucks do not cut ties with defectors adds to recent evidence (Wang et al. 2012) against altruistic punishment and for the notion that cooperation is sustained by the ability of individuals to direct their attention towards other cooperators (Axelrod 1984). By showing that generalized reciprocity is a stronger process than direct reciprocity, we provide additional insights into the issue of how cooperation scales up from dyadic interactions to larger group dynamics (Boyd and Richardson 1988).

Our method offers a new approach to resolving the longstanding controversy about the evolution of cooperation, however the work does have limitations. We demonstrate our approach using data from a unique context—food trucks on Twitter. Although our estimates should generalize to the evolution of cooperation in similar contexts, they are not conclusions about what strategies are more or less influential in general. Our methods for identifying and estimating strategies, however, are generalizable and can be used to model cooperation dynamics in a variety of human and animal settings.

Previous research has taken a reductionist view of cooperation—focused on finding the most successful strategy for its evolution under a wide range of theoretical conditions. In contrast, our results demonstrate that real social systems involve multiple, interrelated mechanisms (Butts 2008). We demonstrate that cooperation is shaped by the joint effects of a set of nine different strategies and future research should identify additional candidates. In real-world interactions, individuals do not rely on a single decision rule or strategy. They also do not have a strategy for every possible situation. Rather, individuals make do with a set of strategies that are mutually supporting because they have complementary strengths and weaknesses. We encourage future research examining the interplay of strategies in greater detail and untangling the benefits of overlapping functions from the dissimilar patterns that allow them to compensate for each other's shortcomings.

The idea that social order might arise from the unintended actions of individuals has a long history in the social sciences. More generally, our results show the potential of methods based on large scale observations of micro-level behaviors to uncover hidden social processes.

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Figure 1: Example of our modeling approach

Observed interaction

Time	**Sender**	**Receiver**
1	A	B
1	B	A
1	B	B

Simulation

Time	Sender	Receiver	Cooperation Shift
1	A	B	
1	A	A	
1	B	B	
1	B	A	
2	B	A	AB-BA
2	A	A	AB-AA
2	A	B	AB-AB
2	B	B	AB-BB
3	B	B	BA-BB
3	A	A	BA-AA
3	A	B	BA-AB
3	B	A	BA-BA

Consider two trucks, A and B, interacting over three time steps. We observe that the following sequence occurs: Time 1: A promotes B, Time 2: B promotes A, Time 3: B promotes B.

We identify all possible pairs of senders and receivers. As there are two trucks, for each time step, there are thus four possible pairs of senders and receivers: AA and BB, where each truck promotes itself, and AB and BA, where each truck promotes the other. (Pairs that were possible but did not occur are shaded in above illustration.)

Given that at time 1, we observe the pair AB, we then simulate the possible cooperation shifts that could occur at time 2. For instance, if pair AA were to occur at time 2, then the cooperation shift AB-AA would occur. The possible cooperation shifts at time 2 are AB-AA, AB-AB, AB-BB, and the shift we observe, AB-BA, the Direct Reciprocity effect.

At time 2, the pair BA occurs, so at time 3, we now simulate the possible cooperation shifts that could occur, based on the BA action that took place at time 2. At time 3, the possible cooperation shifts are BA-AA, BA-AB, BA-BA, and the shift we observe BA-BB.

Figure 2, Panel A: Increase in cooperative trucks and cooperative Tweets, per month

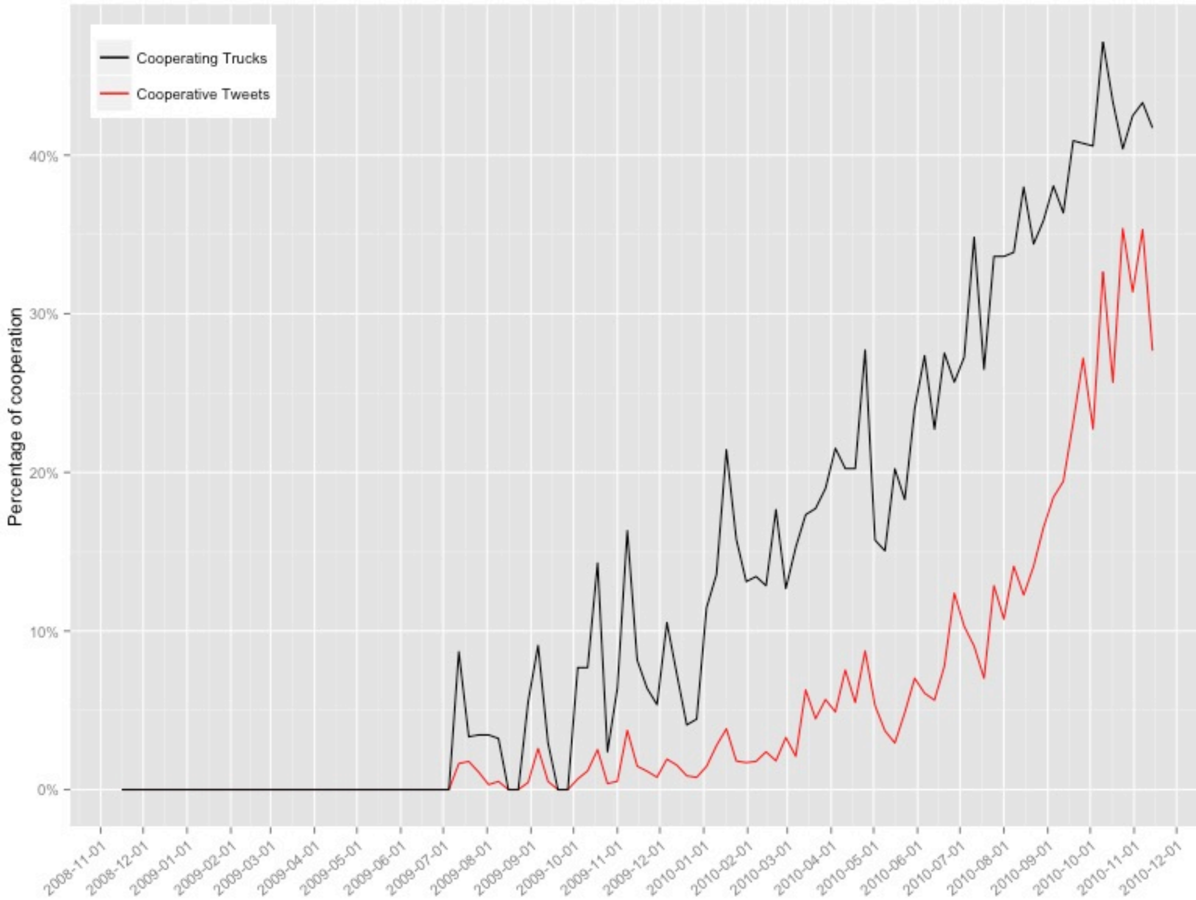

Figure 2, Panel B: Trucks ranked by the fraction of cooperative actions

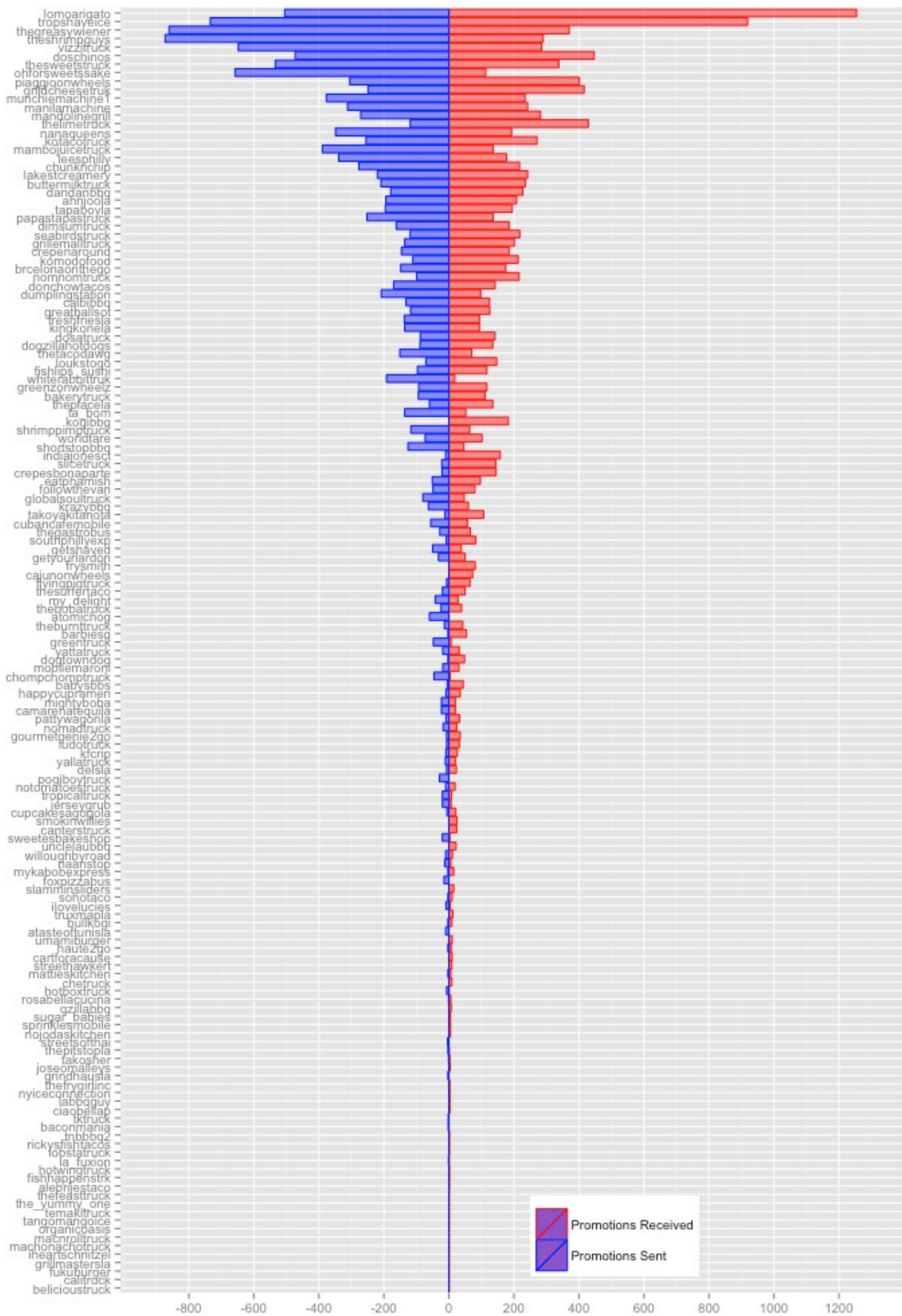

Figure 3: Cooperation network after two years.
Cooperating trucks (who sent at least one promotion) are blue; Defecting trucks are green. 60 isolated defectors are at the periphery of the network. 112 cooperators are in a cluster with the 39 defectors who received at least one promotion from a cooperator.

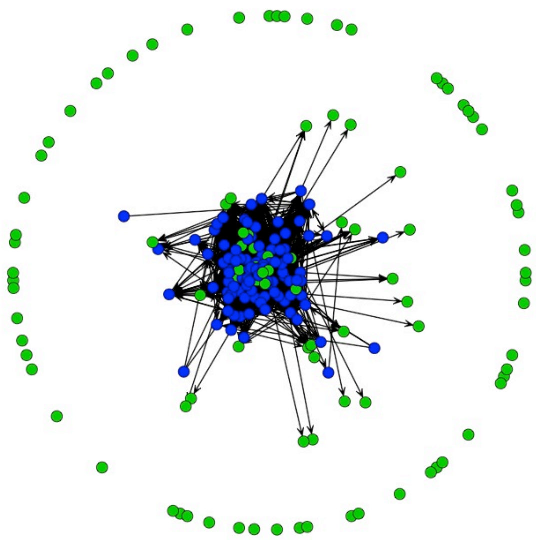

Figure 4: Frequency of ties that involve two cooperators or one cooperator and one defector, by month

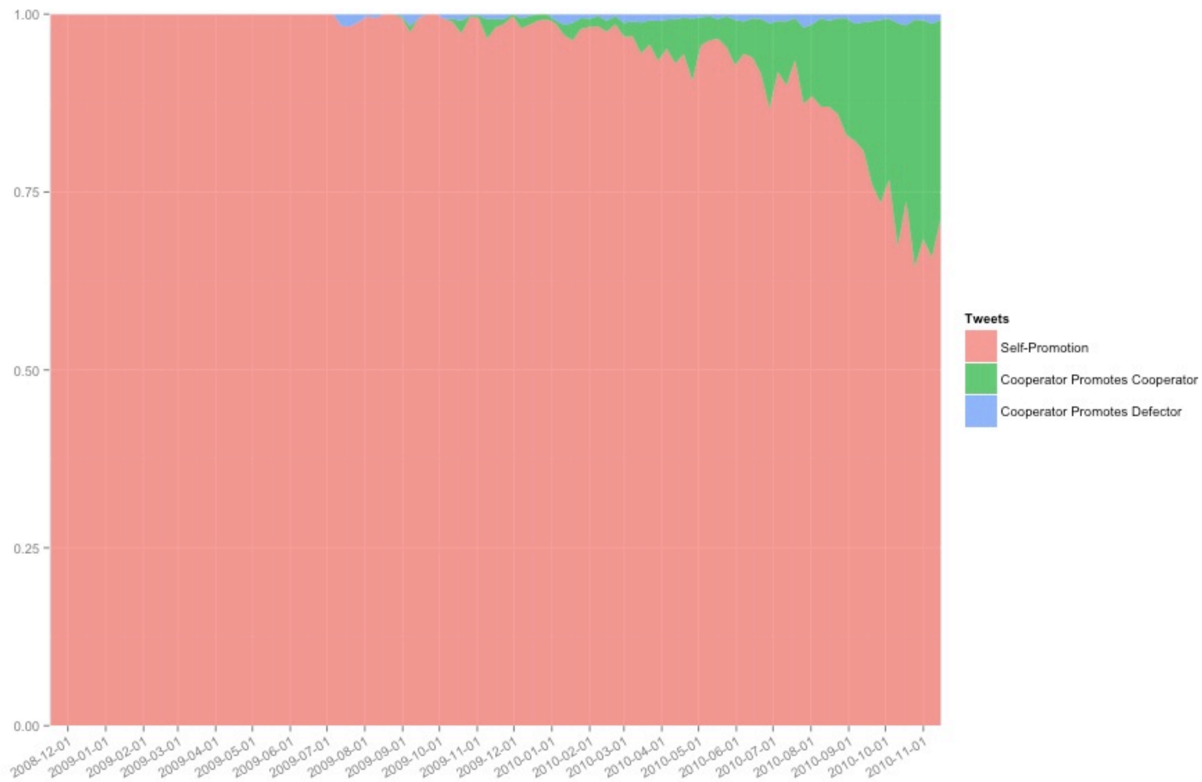

Figure 5: Frequency of cooperation shifts, by month

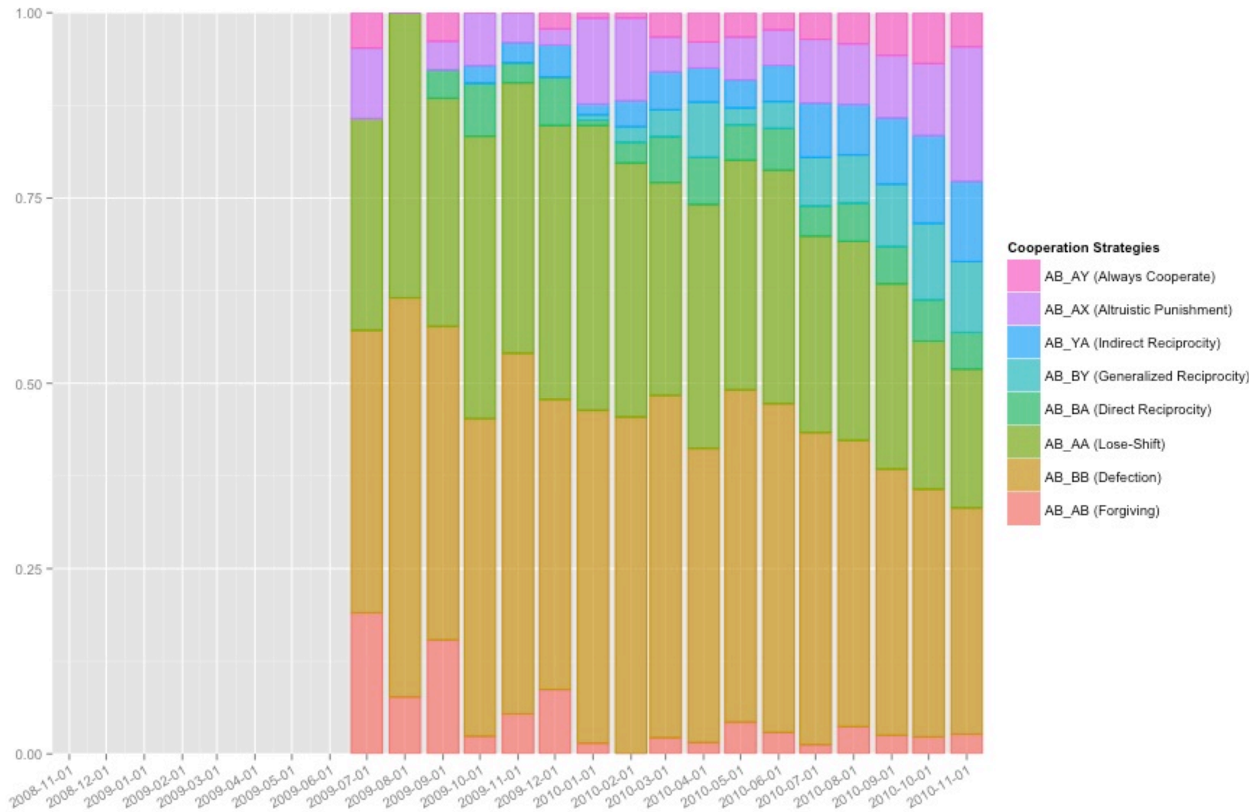

Table 1: Inventory of Cooperation Shifts with examples and frequencies
This cooperation shift inventory can be thought of as a menu of strategies that players can use in the game. Column 5 shows the frequencies for each of the cooperation shifts: how often we observed each strategy in our data.

Cooperation Shift	Notation	Example	Representative Publication	Frequency
Selfish	AA-AA	John promotes himself, then John promotes himself	Axelrod and Hamilton 1981	80747
Forgiving	AB-AB	John promotes Mary, Mary does not reciprocate, John promotes Mary again	Molander 1985; Nowak and Sigmund 1992	368
Always Cooperate	AB-AY	John promotes Mary, Mary does not reciprocate, then John promotes Irene	Axelrod 1984	698
Defection	AB-BB	John promotes Mary, Mary does not reciprocate, Mary promotes herself	Axelrod and Hamilton 1981	5141
Lose-Shift	AB-AA	John promotes Mary, Mary does not reciprocate, John promotes himself	Nowak and Sigmund 1993	3386
Direct Reciprocity	AB-BA	John promotes Mary, then Mary promotes John	Axelrod and Hamilton 1981; Trivers 1971	723
Generalized Reciprocity	AB-BY	John promotes Mary, then Mary promotes Irene	Gray, Ward, and Norton 2012; Hamilton and Taborsky 2005	1135
Indirect Reciprocity	AB-YA	John promotes Mary, then Irene promotes John	Nowak and Sigmund 1998; 2005	1271
Altruistic Punishment	AB-AX	John promotes Mary, Mary does not reciprocate, John cuts ties with Mary	Fehr and Gächter 2002	1478

Table 2: Model estimates

	Controls (1)	Strategies + Controls (2)
Strategies		
AA-AA (Selfish)		2.81*** (0.02)
AB-AB (Forgiving)		.16*** (.01)
AB-AY (Always Cooperate)		.26*** (.01)
AB-BB (Defection)		.74*** (.01)
AB-AA (Lose Shift)		.65*** (.01)
AB-BA (Direct Reciprocity)		.2*** (.01)
AB-BY (Generalized Reciprocity)		.25*** (.01)
AB-YA (Indirect Reciprocity)		.13*** (.01)
AB-AX (Altruistic Punishment)		-.07*** (.01)
Control variables		
Complement	-1.16*** (.01)	.17*** (.01)
Direct Competitor	-.6*** (.01)	-.03. (.02)
Same Commissary	-.52*** (.01)	.19*** (.01)
Activity	.64*** (.01)	.34*** (.01)
Sequential Tweets	.84*** (.01)	.97*** (.01)
Goodness of fit		
Null Deviance	342,364	
Residual Deviance (-2LL)	251,125.6 (df=5)	27,286.83 (df=14)

Note: The numbers in parentheses are the standard errors for the parameters.
* indicates p <.05, ** indicates p <.01, *** indicates p <.001

Supplementary Materials for

Identifying Strategies for the Evolution of Cooperation in Social Networks

Materials and Methods

Data construction

We define a gourmet food truck as a restaurant that operates from a truck and uses Twitter to interact with customers. We define the food truck network as a set consisting of all gourmet food trucks in operation in Southern California during a two year observation period beginning with the launch of the first truck, Kogi BBQ, on November 20, 2008. We obtained lists of food trucks including name, product category, and Twitter user name from two industry databases—RoamingHunger and FoodTruckMaps. We identified 211 trucks in operation during the observation period. A Twitter data reseller, GNIP, provided all of the Tweets from each of the trucks, 152,312 Tweets in total.

Food trucks are required to park nightly at commissaries, which are garages with shared cleaning, food preparation, and storage facilities. The address of the commissary that each truck uses is stenciled on its side. Using Google Images, we found photos of the food trucks, which we then used to obtain the address of each truck's commissary. The 211 trucks park at 61 commissaries. To cross-check the accuracy of the information, we obtained Los Angeles Health Department inspection and permit records, which contain the commissary address of the truck. The information from the two sources is highly consistent, which ensures the quality of the data.

The data was prepared as follows. We first removed any Tweets that were direct messages, as these are not visible to a truck's followers and therefore cannot be classified as promotions. We then identified the sender and receiver of each Tweet. We consider the sender to be the truck that sent the Tweet. When the Tweet mentions another truck—denoted by the "@"

symbol and the mentioned truck's Twitter account name—we classify the mentioned truck as the receiver. Following Butts' preparation of radio transmissions (2008) and Quintane and colleagues' preparation of email communications (2013), we duplicate a Tweet when it mentions multiple trucks, creating an additional tie for each unique receiver. The duplicated Tweets are inserted in the sequence of Twitter messages in the order in which the receiver was mentioned. When the Tweet does not promote another truck, we consider this a self-loop and label the receiver as the same as the sender. Following data preparation, the resulting network consists of 103,585 directed ties. For Figure 3, the graph of the cooperation network, we remove the self-loops and use a network consisting of 14,103 directed ties.

All variables except *AB-AX* are coded using two years of data. *AB-AX*, the cooperation shift for altruistic punishment, captures a pattern where A promotes B, B does not reciprocate, and then A cuts off all further contact with B. We use a third year of Twitter data in calculating *AB-AX* because of truncation. If we do not use Tweets beyond the second year, then many relations in the network will be incorrectly identified as *AB-AX* because no further contact is observed.

We follow Quintane and colleagues (2014) in standardizing all variables to facilitate comparison across models.

Case-control design

The ordinal version of a relational event model amounts to estimating across all sets a conditional multinomial logistic regression model for the probability that of each set consisting of the sender-receiver pair that occurred and all possible sender-receiver pairs, it is indeed the sender-receiver pair that occurred (Butts 2008). In practice, this can be computationally demanding. With 211 possible senders and receivers, each set has 44,521 possible sender-receiver pairs. We observe 103,585 sender-receiver pairs that occurred and thus 103,585 sets. A full database would contain over 4 billion observations. Many of our variables are time-varying, making it extremely demanding to code all variables for every potential sender-receiver pair over the full data sequence.

We use a case-control design to reduce computation time. Other studies using a relational event framework have found that using a reduced set of possible sender-receiver pairs does not affect model estimates (Quintane et al. 2013). For each set, we randomly select five controls from the set of all possible sender-receiver pairs. We consider a truck as a potential sender or receiver once it has started Tweeting. A higher control-to-case ratio generates little gain in statistical efficiency (Donkers et al. 2003; Gail et al. 1976; Ury 1975). This reduces our database from over 4 billion observations to 621,510.

Alternative data transformation

One methodological consideration is how to handle Tweets with multiple receivers. The approach used for our model follows previous research (Butts 2008; Quintane et al. 2013). Furthermore, Quintane and colleagues (2013) suggest that transforming what is one type of interaction at a give point in time (a Tweet from one truck to many receivers) into a sequence of interactions of another type (dyads) has little impact on model estimates.

Table S3 presents estimation results from an alternative data transformation. Where a promotion mentions multiple trucks, we do not duplicate the Tweet and discard all receivers after the first mentioned truck. This reduces the number of promotions observed from 14,103 to 6,626. The results are comparable to those in Table 2 except the cooperation shift for direct reciprocity now has a larger effect than the cooperation shift for generalized reciprocity (Wald test, X^2 =

967.5, df = 2). Table S4 provides an explanation for this difference by illustrating how the data transformation method can impact the identification of cooperation shifts.

Supplementary Materials: Tables

Table S1: Descriptive statistics of the control covariates included in the model

Variable	Measure	Mean	Min	Max
Complement	1 = Sender and receiver sell complementary products (tacos + ice cream); otherwise 0	4.9%	0	1
Direct Competitor	1 = Sender and receiver sell the same product (tacos + tacos); otherwise 0	.38%	0	1
Same Commissary	1 = Sender and receiver park at the same commissary; otherwise 0	1.9%	0	1
Activity	Fraction of prior ties in the sequence sent by the sender	-	0	1
Sequential Tweets	1 = AB-AY cooperation shift where sender promotes a truck at time *t* and had promoted a different truck at time *t -1* (pattern results largely from splitting Tweets mentioning multiple trucks); otherwise 0	Frequency: 7853 ties	0	1

Table S2: Parameter estimates for single strategy models. This table presents parameter estimates and standard errors from conditional logistic regressions. The dependent variable is the sender-receiver pair that occurred. The covariates are various strategies and, when noted, control variables. Within a panel, each column represents a different regression. Panel A includes no controls. Panel B controls for the sender and receiver selling complementary products, selling the same product, sharing a commissary, the number of prior ties sent by the sender as a fraction of all prior ties, and sequential tweets.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Panel A: No Controls				
AA-AA	2.22*** (.01)								
AB-AB		.08*** (.003)							
AB-AY			-.18*** (.006)						
AB-BB				.43*** (.006)					
AB-AA					.38*** (.008)				
AB-BA						.11*** (.003)			
AB-BY							-.43*** (.007)		
AB-YA								-.1*** (.005)	
AB-AX									.08*** (.002)
Null Deviance	342,364								
Residual Deviance	91,347.25	341,460.1	340,996.3	328,052.7	332,529.2	340,731.5	336,102.4	341,831.4	341,591.5

*** p < .001

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Panel B: All Controls				
AA-AA	2.28*** (.02)								
AB-AB		.13*** (.004)							
AB-AY			-.15*** (.006)						
AB-BB				.41*** (.007)					
AB-AA					.37*** (.009)				
AB-BA						.16*** (.003)			
AB-BY							-.4*** (.007)		
AB-YA								-.16*** (.007)	
AB-AX									.01*** (.004)
Null Deviance	342,364								
Residual Deviance	59,554.58	257,283	257,988.7	247,520.6	250,894.8	256,355	254,193.2	257,954.5	258,792.4

*** p < .001

Table S3: Parameter estimates for models without multi-receiver Tweets.

	Controls (1)	Strategies + Controls (2)
Strategies		
AA-AA		2.92*** (.02)
AB-AB		.24*** (.008)
AB-AY		.22*** (.009)
AB-BB		.61*** (.01)
AB-AA		.70*** (.01)
AB-BA		.18*** (.007)
AB-BY		.16*** (.009)
AB-YA		.14*** (.009)
AB-AX		-.03*** (.009)
Control variables		
Complement	-1.16*** (.009)	.23*** (.01)
Direct Competitor	-.63*** (.01)	-.02 (.01)
Same Commissary	-.57*** (.008)	.19*** (.01)
Activity	.71*** (0.01)	.34*** (.01)
Sequential Tweets	.09*** (.003)	.15*** (.006)
Goodness of fit		
Null Deviance	345,154	
Residual Deviance (-2LL)	269,694.2 (df=5)	26,329.03 (df=14)

Note: The numbers in parentheses are the standard errors for the parameters.
* indicates p <.05, ** indicates p <.01, *** indicates p <.001

Table S4: Illustration of choice of data transformation method on generalized reciprocity. This table illustrates how the transformation of Tweets mentioning multiple trucks can impact the frequency with which cooperation shifts occur. We consider a scenario where truck 1 sends a Tweet mentioning trucks 2 and 3. This message is then retweeted by truck 2 and then retweeted by truck 3. Column 2 shows the data transformation used in the model presented in table 2; in other words, how Tweets with multiple receivers are split into sender-receiver dyads. Column 3 identifies the cooperation shifts. Column 4 presents an alternative data transformation method used in the model presented in table S3. Column 5 identifies the cooperation shifts under this alternative data transformation method.

Twitter data sequence*	Data transformation (table 2)	Cooperation shifts	Alternative data transformation (table S3)	Cooperation shifts for alternative data transformation
@getshaved: "Check it out...@lakidstuff posted a nice little blurb about us and our friends @coolhaus and @sprinklesmobile - http://bit.ly/DLa9D."	@getshaved - @coolhaus		@getshaved - @coolhaus	
	@getshaved - @sprinklesmobile			
@coolhaus: "RT @getshaved: Check it out...@lakidstuff posted a nice little blurb about us and our friends @coolhaus and @sprinklesmobile - http://bit.ly/DLa9D."	@coolhaus - @getshaved	AB-BA (direct reciprocity)	@coolhaus - @getshaved	AB-BA (direct reciprocity)
	@coolhaus - @sprinklesmobile	AB-AY (sequential Tweets)		
@sprinklesmobile: "RT @getshaved: Check it out...@lakidstuff posted a nice little blurb about us and our friends @coolhaus and @sprinklesmobile - http://bit.ly/DLa9D."	@sprinklesmobile - @getshaved	AB-BY (generalized reciprocity)	@sprinklesmobile - @getshaved	
	@sprinklesmobile - @coolhaus	AB-AY (sequential Tweets)		

* Note: @lakidstuff is not a food truck and so is excluded in this example.