The Value of Grocery Delivery and the Role of Offline Complements

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Abstract

The growth of the online economy can either reinforce or attenuate disparities in access to retail depending on the nature of its interaction with consumers' offline vicinity. This paper measures the welfare value of new online grocery services and identifies the channels through which consumers benefit from this innovation. I construct a new dataset with the roll-out of two grocery delivery platforms to show how their different delivery logistics affect consumers. I combine this geographic entry information with scanner data to estimate a Revealed Preference model where consumers choose over bundles of products and retailers. I find the new services to be worth on average $120/year to users. If delivery logistics rely on partnerships with local stores, households that live close to multiple retail stores are the most likely to gain access to the new technology. This complementarity between the delivery service and the consumer's geographic location benefits high income zip codes 34% more than low income zip codes due to differences in the supply of offline retail. On the other hand, distance to brick-and-mortar retail makes delivery a more valuable substitute to the offline economy. The value creation through this channel is 26% larger in low income zip codes compared to high income ones. *

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JEL Classification: L81, D69, C23

*Department of Economics, University of Minnesota, Twin Cities. 1925 Fourth South Street, Minneapolis, MN 55455. Email: rabel005@umn.edu. Website: https://sites.google.com/umn.edu/vitoria-r-de-castro Researcher(s) own analyses calculated (or derived) based in part on data from The Nielsen Company (US), LLC and marketing databases provided through the Nielsen Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business.The conclusions drawn from the Nielsen data are those of the researcher(s) and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein. Previous versions of this paper have been circulated under the titles "The Value of Convenience" and "The Value of Same-Day Delivery". I would like to thank Amil Petrin Thomas Holmes and Joel Waldfogel for the invaluable advice. I'm also grateful to all the participants at the Applied Microeconomics workshop at the University of Minnesota for their comments.

I. INTRODUCTION

In 2016, e-commerce accounted for nearly 10% of retail sales, doubling its size in just 5 years (2011-2016)[1]. However, this trend is led by a few product categories with high online shares - such as furniture, clothing and electronics - while most product categories remain exclusively bought offline. Online groceries, in particular, had a share of only 3 percent of total grocery sales in 2016[2]. The first fully integrated internet grocery operations started in 1996 and, only 3 years later, went bankrupt. Consequently, this entire market failed to significantly take-off then. 15 years later, same-day delivery services make use of new technologies to recreate similar operations. These services combine, in a single online medium, multiple retailers and unprecedented speed of delivery due to a unified distribution system. As a result, this new shopping channel promotes benefits to consumers that previous internet grocery operations did not.

The rapid growth of e-commerce and its impact on brick-and-mortar retail have attracted a lot of research interest: (Goldmanis et al. 2010), (Brown and Goolsbee 2002), (Zentner 2008), (George and Waldfogel 2006), (Pozzi 2013). However, the main characteristics of this phenomenon - such as speed of delivery - have massively changed over time. Indeed, as online retailers have recently started making use of new technologies, delivery times for many product categories has shifted from days to hours. This change in fundamental characteristics of e-commerce is crucial for determining the size of benefits generated to consumers and which sectors if retail will be affected going forward.

This jump is speed of delivery is marked by the creation of new services such as *Instacart (2012), Google Express (2013), Prime Now (2014)* and *AmazonFresh (2013)*. Traditional retailers such as Walmart and Target have also been making huge investments in same-day delivery, notably for grocery products. This represents an important shift in the perception of the importance of speed of delivery for the success on an online grocery operation relative to the initial efforts of big-box retailers to create online alternatives, as studied in (Pozzi 2013). In the recent past, Walmart has partnered driver services such as Uber for last-mile fulfillment and more recently acquired the delivery company Parcel[3]. Target also engaged in the

[1] Source: Census 2016.

[2] Source: Statista (https://www.statista.com/statistics/531189/online-grocery-market-share-united-states/).

[3] Sources: https://www.reuters.com/article/us-walmart-grocery-delivery-exclusive/exclusive-walmarts-grocery-delivery-partnerships-with-uber-lyft-fail-to-take-off-idUSKBN1I91S4
https://corporate.walmart.com/article/walmart-announces-the-acquisition-of-parcel-a-technology-based-same-day-and-last-

acquisition of the grocery delivery service Shipt with the same purpose[4]. Speed of delivery and online supply of grocery products are the key common features shared by these services. However, these services differ substantially in ways that affect both the welfare of consumers and the toll imposed on traditional offline retail sectors. Indeed, while some of these firms operate exclusively as online retailers and represent a substitute to the traditional channels, others rely on partnerships with local stores, displaying some complementary with the local economy (see section (II)). A platform that makes use of local stores to fulfill deliveries will offer a service of better quality in areas that already display large offline variety. For this reason, geographic inequalities in retail supply can be intensified by this new technology. Conversely, in the absence of complementarity, the growth of e-commerce can attenuate some inequalities in the access to retail and, in particular, to groceries. This matters not only to determine the effects of e-commerce on the retailing sector but, also to identify consumers that benefit the most from the online economy.

I use the roll-out of two major same-day delivery services in 27 metro areas to study the impact of these new alternatives on consumers' retailer choice and welfare. Due to retailer confidentiality concerns with the Nielsen data, I will not refer to the services by their names. Instead, I will refer to them as *Blue* firm and *Green* firm. These firms have been expanding across the country since 2012. And, most of the launches took place in the period of 2014-2017, for both firms (see figure (1)). The demand analysis relies on observed purchases during the period of 2015-2016. There are important characteristics that distinguish Blue and Green firm: even though these services are very similar in terms of their entry patterns across the country and the type of delivery service offered, they differ a lot in terms of their geographic entry patterns within metro areas (zip codes served)(figure (3)) and their interaction with brick-and-mortar retail. Green firm is an online shopping platform that fulfills deliveries for brick-and-mortar grocers, discount stores and drug stores with which they share a partnership contract. Blue firm does not rely on this type of offline partnership as it uses its own dedicated distribution centers. Hence, while the former delivers a subset of products from pre-existing stores located within a certain radius from costumers, the latter operates as typical online retailer. For this reason, Green firm is to some extent a complement to offline retail and Blue firm is a substitute. Comparing the behavior of households across these two platforms can shed light

mile-delivery-company

[4]https://corporate.target.com/press/releases/2017/12/target-to-acquire-same-day-delivery-platform-shipt.

into important questions regarding the interactions between online and offline retail. Additionally, the launch of these services is the ideal event to isolate the convenience dimension of e-commerce. Indeed, e-commerce is a phenomenon that provides, at the same time, an increase in the variety of products that consumers have access to and an increase in consumers' convenience in getting access to these products (Einav et al. 2017). These services, however, only offer a subset of products that were already previously available to consumers either online (at an inferior speed of delivery) or offline (at brick-and-mortar stores located at a variable distance). Therefore, they represent an important shift in the convenience component of e-commerce rather than increase in access to different product varieties.

This paper is related to the literature that studies the impact of e-commerce on different sectors of offline retail. There is, in particular, a lot of evidence on the impact of the diffusion of e-commerce on very specialized businesses, such as book stores and music stores: (Zentner 2008),(George and Waldfogel 2006). In this paper, I study how new online alternatives (same-day delivery services) can generate heterogeneous welfare gains to consumers depending on the nature of their interaction with offline retail. This relates to a literature on e-commerce and spatial differentiation and, specifically to the work in (Leamer and Storper 2001), (Pozzi 2013), (Forman, Ghose, and Goldfarb 2009) and (Sinai and Waldfogel 2004). The latter finds that the Internet is a substitute for proximity to retail outlets. And, (Pozzi 2013) points out specifically the role of online grocery shopping in lifting the constraints of geographical location. The results in this paper show that a new variety of e-commerce represented by grocery delivery platforms can lift some constraints in access to retail but, also identifies limitations. I find that the services of both Blue and Green firm are *less* valuable for consumers that live in areas with high density of retail within 1 mile. However, the Green firm's service is *more* valuable the more offline retail partners it offers in the consumer's zip code. One additional brick-and-mortar alternative within 1 mile *reduces* the value attributed to the Green service by approximately $\$1$ per purchase. But, an additional offline partner *increases* the value of the same service by approximately $\$1.4$ per purchase. Because deliveries are made from the partner's store, additional partners can only be offered to consumers located close to the store. This means that, to some extent, this service is a complement to the consumer's offline retail vicinity and, consequently, is limited in its ability to reduce consumers' geographical constraints in access to groceries. More generally, this implies that even though these new services can play an important role in increasing consumer access to retail in areas with low offline retail density, differences across business models are important to determining the size of benefits. Specifically, a delivery service that relies on brick-and-mortar stores to fulfill deliveries provides limited benefits for individuals whose access to consumption alternatives is most limited.

By investigating how online alternatives affect low-income households' access to groceries, this paper also relates to the literature on *"food deserts"* - areas with low availability or high prices for food. A large portion of this literature has focused on documenting disparities in the supply of retail, notably of large grocery and supermarket chains, between low and high income neighborhoods: (Powell et al. 2007), (Besharov, Bitler, and Haider 2011), (Alwitt and Donley 1997), (Algert, Agrawal, and Lewis 2006), (Walker, Keane, and Burke 2010) and (Nayga and Weinberg 1999). However, new evidence in both (Handbury, Rahkovsky, and Schnell 2015) and (Allcott, Diamond, and Dube 2018) ignites the discussion about the role of demand. (Allcott, Diamond, and Dube 2018) find that exposing low-income households to the same availability and prices experienced by high-income households reduces nutritional inequality by only 9%. This means that 91% of the differences observed in nutritional patterns between those two groups are driven by differences in demand, and not lack of supply. This paper contributes to this literature by providing evidence on how shopping for groceries online can be a substitute for traditional retail channels, depending on users' income and location in the city and showing to which extent online retail can help attenuate the issue of access to retail.

This paper also contributes to the discussion raised by (Einav et al. 2017) on the different ways that e-commerce generates value to consumers and how to measure it. (Einav et al. 2017) provide a framework to separate the two main components of the welfare value of e-commerce: variety and convenience creation. I propose an identification strategy to single-out the convenience component of the value of online retail and measure it. This paper contributes to the understanding of the determinants of retailer choice and demand for online delivery. By having a better understanding of the role of speed of delivery on consumers' decision of where to shop, we can make considerations about which types of brick-and-mortar retailers are the biggest losers in this most recent phase of e-commerce. I also add to the discussion on the relative importance of convenience in determining online demand. (Houde, Newberry, and Seim 2017) present a location decision model similar to (Holmes 2011) that expresses the trade-off between demand-driven revenues gains and tax-related revenue losses from Amazon's decision to build new distribution centers. In their model, being closer to consumers matters for the retailer due to savings in shipping expenses. This paper presents evidence that the online retailer's proximity, in terms of delivery time, is also an important determinant of demand.

Finally, this work is also related to the store choice literature. I use a modern technique of partial identification from (Pakes et al. 2015) and a setup of optimal consumer choice from (Katz 2007) to overcome the classic challenges that arise when estimating consumers' store choice problem. These challenges are rooted in the fact that, when choosing which store to visit, consumers also take into account the set of products to be bought and expected prices. Additionally, households' choice sets differ with their geographic location, making the econometrician's job to specify all the possible alternatives very difficult. The store choice problem is an intrinsically discrete one and, there is a large literature on store choice, notably of supermarket choice, that uses discrete choice and discrete-continuous methods[5]. However, the estimation with discrete choice methods requires that the entire choice set be explicitly known for all individuals, which generates both computational and specification concerns. When the store choice is combined with a bundle choice, the dimensionality of the choice set will be a problem and assumptions to reduce the dimensionality of this set can cause serious specification error. For that reason, I choose a partial identification strategy with a moment inequality estimator to allow for a more flexible specification and less stringent assumptions. I apply the framework first used by (Katz 2007) to a setting where households also have a variety of online retailing options and have heterogeneous demand for these alternatives as well as heterogeneous travel costs.

II. Institutional Details

In this section, I provide relevant details about the same-day delivery market. There is a large variety of delivery services, most of which specialized in grocery delivery. Most of them are constrained to one region of the US, concentrated in not more than a handful of large metropolitan areas. The two services that are studied in this paper have a nation-wide presence and, at the same time, a speed of delivery in the

[5] Some examples of store and retail chain choice using such models include (Smith 2004), (Ellickson and Arie 2005) and (Hausman and Leibtag 2004).

order of hours. This nation-wide scale makes the geographic richness of the data on entry patterns of the two firms and consumer choices quite unique.

Typically, grocery delivery services have subscription plans. Costumers pay a yearly or monthly flat-rate fee and get unlimited deliveries for that period. There is, however, a lot of heterogeneity in business models. A lot of services deliver only from one large brick-and-mortar retailer. Examples of large retailers that have their own delivery service include Walmart, Costco and, more recently, Target and Sam's Club. Many smaller grocery chains also offer their own delivery or pick-up services. Another type of delivery service business model are online platforms that specialize in fulfillment and operate through partnerships with multiple local stores. Examples include: Instacart, Peapod and Google Express. Finally, there are delivery platforms that are typical online retailers operating centralized distribution systems, making deliveries from a warehouse. This is the case for Amazon's Prime Now and Amazon Fresh as well as Jet.com. The firms studied in this paper represent two of these distinct business models: Green operates through partnerships with local stores and Blue is a traditional online retailer with specialized distribution centers. Both have subscription services. Blue's subscription is bundled with a multitude of other services offered by the same online retailer and is a pre-requisite to use the service. However, Green can be used without a subscription at the cost of a per-trip fee. For both services, annual fees range between $100-150 and Green's trip-based fees range between $5-8. The actual cost of the service will depend on whether the household has a subscription or not. Since that information is missing for the households in my sample, I approximate the cost of Blue dividing the yearly cost of the subscription by the average number of trips made by users in a year. For the Green firm, I use the trip-based fee. Those two fees are included in the cost of the bundle when estimating the model in section (V).

III. DATA

The first data source used in this paper is the Nielsen Consumer Panel Dataset, henceforth Homescan. This is a transaction-level dataset that spans 2004-2016, including around 60,000 households annually. For each shopping trip made by panelists, there is detailed information on the products purchased - including UPC code and description as well as price paid. Panelists also report the retailer, the location of the store visited and the type of store (e.g. Grocery, Department store, Online Shopping, Discount Store and Drug Store). The data also includes household characteristics such as income brackets, presence of children in the household, age and education of heads of household, city and zip code.

A variety of data sources are used to construct a panel of availability of the two delivery services over time and by zip code. The first source is public information available on the official websites of both online platforms. These two sources are scraped to get the set of zip codes served, once the service is available in a given metro area. Then, press releases, newspapers and social media pages are used to recover the exact launch dates for each metro area[6]. With this, I construct a panel that spans 2012-2017 and includes 32 US metropolitan areas and tens of thousands of zip codes.

Finally, I match households in the Nielsen Homescan to the services' availability dataset using their zip code. Figure (3) shows an example of the resulting delivery coverage by zip code for a metro area in the sample in 2015. The zip codes in blue are exclusively served by the Blue firm, the ones in light green are exclusively served by the Green firm and the ones in dark green are served by both firms. Hence, the households located inside each colored area gain one or two same-day delivery alternatives over the observed period in the data (2015-2016). There are only 4 metro areas for which either both launches or the only launch in that location occurred prior to 2015 and there is one metro area where there was a launch during this period but, no users in that city appear in the data. Hence, I work with 27 metro areas that include 680 zip codes served by Blue firm, corresponding to 4,708 households in the Homescan and, 640 zip codes served by the Green firm, corresponding to 4,693 households in the Homescan. A subset of these households are users of one or both services and their purchases through these new retail alternatives are observed in the data. I will omit the exact number of Nielsen panelists that are users of each same-day delivery service for data confidentiality reasons. The data used to estimate the model in section (V) includes all purchases from retailers Blue and Green as well as a random sample of purchases made through other retailers by both users and non-users of the same-day delivery services.

Data on zip code characteristics is also used to complement information on availability of retailing

[6]The Green firm actually makes gradual expansions within the metro areas in the years after the first launch. For that reason, I use the firms' social media posts to recover the exact launch dates by neighborhood.

alternatives for households. To that end, I use the Zip Code Business Patterns 2016 (ZBP). This dataset provides a count of establishments by NAICS code for every zip code in a given year. The ZBP data are drawn from tax records, the U.S. Census Company Organization Survey, and other administrative data. I use this data to construct the number of relevant retailing alternatives within a 1 and 5 miles radius of each household by computing straight-line distances between the geocoded centroid of every zip code in the data and all other zip codes within those radius. Then, for every household zip code, I sum the number of retailers in the relevant NAICS codes located within those two radius. These pair-wise distances between zip codes are also used to compute distances traveled by consumers to the stores they visit. The Homescan contains 5-digit zip codes for households but only 3-digit ones for stores, for privacy concerns. So, stores visited are assumed to be located the closest 5-digit zip code that starts with the 3-digits provided for that store in the Homescan.

The empirical strategy consists of exploring the before and after shopping behavior of households that gain access and use same-day delivery services. At the same time, non-users of the services within the delivery radius of the services and households in near-by zip codes that fall just outside of the delivery radius are used to control for time confounders. The following section provides further details on this strategy.

IV. Regression Analysis and Empirical Strategy

i. Substitution of Offline Channels

In this section, I provide an empirical strategy to identify the causal effect of the availability of same-day delivery on households' choice of retail channel. The strategy consists in looking at the frequency of shopping trips to different types of retailing channels made by households who use the services Blue and Green, before and after each service is launched. Figure (2) shows how the timing of when purchases from these new retailers first appear in the Homescan lines-up with the launch dates collected (time 0). For users of each service that are located in different metro areas, the date in which each service is made available will be different. Moreover, within the same metro areas, there are households located in adjacent zip codes where one of these zip codes falls within a service's delivery radius and the other does not. Hence, at a given period t, the sample contains: households that have access to one or two services and households that have access to none. The latter is divided between the two previously mentioned groups: households that will in some later period be served by Green and/or Blue and households that will not but, live close to some that do. These two types of non-served households are used to control for time confounders that can be associated with oscillations in a retail channel's attractiveness in a given period. Meanwhile, the effect of interest is driven by changes in choices across retail channels for households that become users of the new services once they become available.

The regression analysis uses the same retail channels used to estimate the revealed preference model in section (V): Grocery Stores, Discount Stores and Drug Stores. Those are the most likely channels to be close substitutes to same-day online delivery services. The purpose of this exercise is twofold: firstly, to check the existence of a direct substitution between those channels and the new alternatives and, secondly, to point out shopping pattern differences that exist between households of distinct income levels.

The regression estimated is the following:

$$Pr(Channel_{it} = j) = \beta_0 + \beta_1 * \mathbf{1}_{Green_{it}} + \beta_2 * \mathbf{1}_{Blue_{it}} + \alpha_i + \alpha_t + \epsilon_{it} \tag{1}$$

An observation is a purchase made by household i in period t. The regression above is done for each channel type and income group separately. Hence, in each regression, the dependent variable is a dummy equal to 1 for each observation in the data corresponding to a shopping trip associated with that channel. I regress this dummy, for each channel and each income group, on two indicator variables: one for Blue and one for Green firm. Each service indicator has to satisfy three conditions: the service has to be available in user i's metro area at time t, i's zip code has to be within that service's delivery radius and i has to be a user of that service[7]. Aside from these two variables of interest, all regressions include household fixed-effects and month-specific fixed-effects. Due to the high number of fixed-effects, I opt for a linear probability model instead of a non-linear approach such as Logit or Probit.

As previously mentioned, there are important differences in the delivery logistics used by each service

[7] A household is defined as a user of a service if they have made a purchase through that service at any point in time.

and their relationship with offline retail. This translates into differences in the zip codes they choose to serve and the type of users they consequently have: table (5) shows how the demographic characteristics of delivery service users differ from the average Nielsen panelist in 2015-2016. The Green firm, as it relies on the pre-existing retailing alternatives in an area, is most likely to enter zip codes that have more grocery stores, discount stores and drug stores. Those are also wealthier zip codes, as can be seen on table (1e). Conversely, by having a centralized distribution system, the Blue firm serves a continuous radius centered in the downtown area of the cities it operates in: as shown in figure (3). This is more likely to include lower income neighborhoods, even if not purposefully. This is reflected on the characteristics of users: Blue firm has a larger share of users who are in the lowest income group ($< 45K$) than the Green firm, as shown in table 5. Moreover, as it is well documented in the food deserts literature, low income households are more likely to shop for groceries at drug stores and discount stores, instead of supermarkets or grocery stores. Whether the reason for this is differences in retail availability or differences in demand across income groups (as posed by (Allcott, Diamond, and Dube 2018)), these features will result in substitution patterns that differ across income groups and the two new services. For this reason, the regressions presented show that channels more likely to be replaced by the new retail alternatives differ across groups.

The regression results are presented in tables (7) - (9). The coefficients on each firm's availability indicator represent the change in the probability that a user of that service buys from a retailer in channel j after the service is available. The launch of the Blue service has effects across all income groups and all three offline channels. Notably, the probability of a household in the lowest income group making a grocery trip falls by 35 percentage points once the delivery service is available. For the highest income group, the Blue service doesn't seem to be a close substitute for grocery trips. However, the Green service is: users of this service in this income group make 33% less grocery trips once this service is available. Discount stores see a drop of 8-11% in trips across all income groups when the Blue service becomes available.

Finally, the logistic differences between Green and Blue firm also impact their product selection. At least during the period between 2015 and 2016, even though Blue firm had a very large catalog of general merchandise as well as dry and frozen groceries, it had a very limited selection of fresh produce. Green firm, however, had multiple partnerships with grocery stores, notably some of the largest in the country and some known for the quality of their fresh produce department. Given that high income households, even when shopping at the same retailer[8], buy 0.62 standard deviation more items in this category, Green firm is a closer substitute for grocery shopping than Blue firm in this income group.

II. Distance to Retail and Use of New Services

In this section, I discuss the role of distance to offline retail as a determinant of demand for new online delivery services. There is large variation in the number retailers available through the Green platform across locations as well as variation in how close consumers are to offline retail, including to stores that have a partnership with Green (see figure (5)). I show how the probability of a consumer using new online delivery services depends on the distance to offline retail substitutes and, in the case of the Green service, how offline partnered stores are - to some extent - complements. I use the number of stores within 1 mile of each consumer to measure the number of alternatives available and use distance to closest Green partner store to identify the existence of substitution between the new service and the retailers it relies on. Since distance to partnered stores also determine availability of the Green service and the number of retailers the consumer can choose on this platform (see figures (6) and (7)), I also control for the number of partners offered through the Green service in the consumer's zip code.

Table (10) shows the result of the linear probability regressions for Green firm. In the most complete specification, the probability that a consumer makes a purchase using the Green service depends on all the variables described above: distance to retail, number of Green partners offered in the consumer's zip code and number of stores within 1 mile. The main endogeneity issue in identifying the effect of proximity to offline retail on use new online services is due to the fact both availability and quality of these new services can also depend on proximity of the consumer to stores. Indeed, controlling for the number of partners in the consumer's zip code impacts the coefficient on distance in the expected direction. According to the most complete specification, a consumer located at 5.6 miles from the closest Green partner store is 0.68 percentage points (approximately 5 standard deviations) more likely to purchase from Green firm than a consumer located within 1 mile. Any additional store (this includes only grocery stores, discount stores and drug stores) within 1 mile also impacts negatively the probability of purchasing from the Green service (0.33 p.p. per store - 2.7 standard deviations). However, having more partners impacts the probability of purchase positively (0.37 p.p or 3 standard deviations per additional alternative offered).

[8] See tables (4a) and (4b)

This means that zip codes that are located closer to partner stores are offered more alternatives within the Green service and, are more likely to use this service for this reason but, the closer they are located to these stores, the less likely they are to use the online service.

Table (11) presents similar results for the Blue service. As this service does not rely on partnerships with local stores, it is strictly a substitute to brick-and-mortar retail. The number of Green partners offered in a zip code and the proximity to Green partner stores both seem to have no effect on the demand for the Blue service. However, the overall number of offline alternatives within 1 mile (0.32 p.p. or 1.8 standard deviations per additional alternative) and the proximity to overall brick-and-mortar alternatives both correlate to the probability of purchasing from the Blue service. An additional store within 1 mile reduces the probability of purchasing from the Blue service by 0.33 percentage points (approximately 1.8 standard deviations).

V. DEMAND MODEL

In this model, consumers make shopping decisions indexed by t. A consumer decides to make a purchase conditionally on some information about prices and their utility of visiting each different retailer. In particular, before choosing a retailer, the consumer observes a random component of their utility associated with each different bundle of products that could be bought in that period: ϵ_b. For each occasion t in which the individual i has decided to shop, she will choose $d = (b, j)$: a bundle (b) and a retailer (j). A bundle is a collection of UPC codes that identify products and the set of retailing alternatives contains all retailers that appear in the data at any point in time. A discrete choice modeling approach to this problem would require specifying every alternative in the choice set - each combination of products in a basket and stores - which makes the problem intractable. Furthermore, specification assumptions to make the problem tractable - such as how the random variable of store visits is distributed, how the decision process takes place and how households form expectations on prices - would be subject to specification error. For this reason, I opt for a revealed preference methodology to avoid avoid unnecessary assumptions that can lead to this type of error. This method consists of comparing the utility value of the optimal choice made by the consumer with other alternatives that could have been chosen to infer bounds on the parameters of interest.

Similarly to (Katz 2007), I will assume that the utility is additively separable into: the utility value of the bundle purchased, the expenditure required to buy b at retailer j and the dis-utility from the drive time to j (if it's a brick-and-mortar retailer). This assumption allows for the partial identification of a subset of parameters (the ones relevant for the store choice), while avoiding the estimation of the parameters associated with the bundle choice. In a shopping trip (b, j) a household spends Exp_{bj}, the cost of bundle b at retailer j. The sensitivity to the bundle cost is allowed to vary with household income, included in the vector of demographics Z. The utility of the trip also depends on retailer characteristics X_j and the distance between the household and retailer j's closest store T_j. In order to not burden the notation, I omit household and trip indexes. Hence, the utility of a shopping trip (b, j) for a consumer with demographic characteristics Z has the general form:

$$U_{jb} = f(\alpha, Exp_{jb}, Z) + g(\beta, Z, X_j) + h(\lambda, Z, T_j) + \xi_j + V(b, \epsilon) \tag{2}$$

Note that the utility of a trip has a component that does not depend on the store choice: $V(b, \epsilon)$. This term can have a deterministic utility component and a random one. It allows for many flexible specifications on the utility of a bundle. For example, it can be as flexible as the utility of the bundle being household specific, allowing every household to value a given bundle b in a unique manner as well as differently for every period through the random component (ϵ). The set of parameters (α) correspond to bundle cost elasticity parameters and β is the set of parameters associated with the store characteristics. Finally, ξ_j is the unobserved retailer quality and λ is the coefficient associated with travel costs, given a distance T_j to retailer j. If the separability assumption holds true, we can compare the utility value associated with each store alternative, holding the bundle fixed. By holding the bundle fixed, the difference in utility across stores is independent of the bundle chosen, reducing the set of parameters to be estimated. To see this, let b denote the bundle bought at store j and $\tilde{b}$ denote the optimal bundle the consumer would have bought at an alternative store k. Let I be the information set of the household when making such decision. By optimality of these choices, we get the following inequality that holds for any bundle at any period:

$$E[U_{jb}|I] \geq E[U_{k\tilde{b}}|I] \tag{3}$$

Additionally, if $\tilde{b}$ is the optimal bundle choice at store k then, for any other bundle - including b - the following inequality also holds true:

$$E[U_{k\tilde{b}}|I] \geq E[U_{kb}|I] \tag{4}$$

By transitivity, joining the last two inequalities yields:

$$E[U_{jb}|I] \geq E[U_{kb}|I] \quad or \quad E[U_{jb}|I] - E[U_{kb}|I] \geq 0 \tag{5}$$

The last inequality is the key implication of consumer behavior used for estimation. It implies that, for any trip (b, j), we can hold the bundle b fixed and compare the utility of this observed choice with the utility of the alternative choice (b, k). Hence, we can write the inequality as the difference between the utility of the chosen option and buying the same bundle at a different store k:

$$E[\Delta U_{b,jk}|I] = E[U_{jb}|I] - E[U_{kb}|I] \tag{6}$$

Using equation (2) and taking the difference between U_{jb} and U_{kb}:

$$E[\Delta U_{b,jk}|I] = E(\Delta f(\alpha, Exp_{b,jk}, Z) + \Delta g(\beta, Z, X_{jk}) + \Delta h(\lambda, Z, T_{jk}) + \Delta \xi_{jk}|I) \geq 0 \tag{7}$$

Just as elaborated in (Katz 2007), this leaves us with a set of utility inequalities that do not depend on the utility of the bundle, as the term $V(b, \epsilon)$ is differenced out by this procedure.

VI. Estimation

I. Specification

The specification used to estimate the model expresses the potential trade-off faced by consumers between distance and price level of stores:

$$\Delta\tilde{U}_{b,jk} = (-\alpha_0 + \alpha_1 Y)\Delta Exp_{b,jk} + \Delta X_{jk}(\beta_0 + Z_1\beta_1) - \Delta T_{jk}(\lambda_0 + Z_2\lambda_1 + \nu_2) \tag{8}$$

Where $\Delta\tilde{U}_{b,jk}$ is the difference in utility between retailers j and k measured by the econometrician. During trip t, consumer i travels a distance T_j (in miles) to a store of retailer j and spends $Exp_{b,j}$ dollars acquiring bundle b. Retailer chain j has an average assortment (number of products for sale) of X_j across its stores and an average unobserved retailer quality of ξ_j, controlled for by a retailer dummy included in the vector X_j. The mean expenditure elasticity (α_0) is normalized to 1, however it is allowed to vary with income Y_i. This normalization means that the remaining parameters have a convenient dollar-value interpretation. For example, λ is the cost in dollars of traveling an extra mile for a shopping trip. The key parameters of interest are the retailer dummies for the new delivery services and their interaction with consumer characteristics Z. The vector of household characteristics includes controls for age, household composition, income, the number of offline substitutes nearby (1 and 5 miles radius) and the dollar value of the bundle purchased (Z_1). Additionally, the travel time variable is also allowed to interact with income dummies, in order to capture differences in mobility across income groups (Z_2).

For every purchase in the data, the counterfactual cost of the bundle purchased is constructed for every retailer chain available in the metro area of that trip and every online retailer option in the data. This is done by using the prices paid for the same UPC by other consumers in other stores. In that way, a mean price is calculated for every UPC at all the retailers where that product is available. Then, for each bundle purchased, the mean prices are used to compute the alternative bundle cost at every retailer. The universe of retailers in the data is the set of retailers that were visited at least once by a Nielsen panelist in the 2015-2016 period. For each trip, counterfactual retailers will be the two closest retailers and the two retailers with most similar cost, resulting in a total of 4 counterfactuals per observation.

II. METHODOLOGY

There are two types of errors than can arise: an *approximation* (measurement) error and an *expectational* error. The former comes from the difference between the returns perceived by the agent and the returns measured by the econometrician. If the utility can be measured up to a mean zero measurement error, then there is no structural disturbance and both expectational and measurement errors enter naturally in the model. An expectational error can be the result of a discrepancy between the bundle used by the consumer to determine her store choice and the bundle used to measure her expenditure: $\nu_{bb'} = (-\alpha_0 + \alpha_1 Y)\Delta Exp_{b,jk} - (-\alpha_0 + \alpha_1 Y)\Delta Exp_{b',jk}$. Conditional on i's information set, $\nu_{bb'}$ has mean zero[9]. Additionally, if this error is uncorrelated with the instrumental variables[10] W:

$$E[\Delta\tilde{U}_{b,jk}|W] = E[\Delta\tilde{U}_{b,jk}] + E[\nu_{bb'}] = E[\Delta U_{b,jk}] \geq 0 \tag{9}$$

There is, however, one dimension of unobserved heterogeneity that can be accounted for. I follow (Katz 2007)'s approach to a random coefficients on the travel cost where ν_{i2} is an idiosyncratic and mean-zero preference shock to the cost of the distance traveled. The methodology used for estimation follows (Pakes et al. 2015). For each parameter in the vector θ, the method yields estimates for the bounds of the identifiable set that includes the true parameter θ^*. The inequality condition in (9) implies:

$$E[\Delta\tilde{U}_{b,jk} \otimes W] \geq 0, \quad \forall k \tag{10}$$

The sample analogue of the moments in (10) is:

$$\tilde{m}_i(V,\theta) = \frac{1}{n_h}\sum_{i=1}^{n_h}\frac{1}{\sqrt{n_i}}\sum_{t=1}^{n_i}\Delta\tilde{U}_{bj} \otimes W_i \tag{11}$$

Where V stands for the data, n_i is the number of trips made by household i and n_h is the number of

[9]Further details in (Katz 2007)

[10]The vector of instrumental variables includes consumer demographics, retailer dummies and a constant.

households. For each element of the parameter vector, the lower bound solves:

$$\min_{\theta \in \Theta} \theta_i \qquad (12)$$
$$s.t. \quad m(V, \theta) \geq 0$$

And the upper bound solves the analogous max problem. Since $\Delta\tilde{U}$ is linear in parameters, so is $m(V, .)$. Hence, the problem above is a simple linear program, where we need to identify matrices (A, b) such that: $m(V, \theta) = A\theta - b \geq 0$. In practice, when the number of constraints is high[11], the probability that all moments are non-negative for a particular sample is very small although, they should be non-negative in expectation. Hence, the estimation is implemented by following this sequence of steps:

- Step 1: Compute $m(V, \theta)$ and recover the matrices A and b that solve $m(V, \theta) = A\theta - b = 0$.

- Step 2: Define the function:

$$m_{neg}(V, \theta) = \sqrt{\sum_{i=1}^{n_h} \sum_{t=1}^{n_i} m_{it}(V, \theta)^2} \quad , \qquad if \quad A\theta - b < 0$$
$$0 \quad , \quad otherwise \qquad (13)$$

- Step 3: Solve:

$$\theta^0 \in \quad argmin_{\theta \in \Theta} \quad m_{neg}(V, \theta) \qquad (14)$$

- Step 4: For each $\theta_i^0 \in \theta^0$, fix θ_{-i}^0 and search for smallest $\tilde{\theta}_i$ such that $m_{neg}(V, (\tilde{\theta}_i, \theta_{-i}^0)) = m_{neg}(V, \theta^0)$. And, analogously for the largest parameter value.

Even though following this procedure can generate a set of parameter estimates, for the specifications presented in Table (12) it yielded point estimates. Estimating point estimates is relatively common when using this version of the method for problems with a large number of moments: (Ho 2009), (Katz 2007) and (Ishii 2005) all get point estimates in their applications. Since the base expenditure elasticity is normalized to 1, all parameter values aside from α are in dollar value.

[11]The number of constraints in the specification with 35 retailers dummies is 216.

Confidence intervals are calculated using the binding moments to approximate the distribution that stochastically dominates $\hat{\theta}$ and bootstrap from this distribution[12] with a confidence interval of 95%.

VII. Results

The estimates for the revealed preference model are presented in tables (12) and (13). The first table shows the results for the parameters where I interact each service dummy (Blue and Green) with household characteristics and the value of the bundle of goods purchased. All parameter estimates in tables (12) and (13) are in dollars per shopping trip and, the estimates of the interactions between demographic variables and each firm's dummy can be directly interpreted as differences in consumer surplus after normalizing by the cost elasticity for that group[13]. I also discuss consumer surplus values per year, using the per trip estimates and the average number of purchases through Blue and Green by their users. The demographic variables inlcuded in the model are motivated by the summary statistics in table (5). Users of the two same-day delivery services are younger than the average panlelist in the sample and the proportion of single females among users is also higher. In columns (1) to (4) of tables (12) and (13), I present results for 4 different specifications. In specifications (1) and (2) I use the number of retailers within 1 and 5 miles as a way of evaluating the complementarity and substitution effects of each service. Column (1) contains the results without the random coefficient on the travel cost (ν_2) and column (2) adds the random coefficient. Then, in specifications (4) and (5) I use the number of partnerships offered by the Green service in the household's zip code and the distance from the household's zip code to the closest retail store as variables. Specification (5) includes the random coefficient (ν_2) and (4) does not. Including the random coefficient has no major effect on most coefficients. As discussed in (Katz 2007), heterogeneity is an important aspect of the travel cost. And, including the random coefficient increases the estimate of the travel cost. It has some effect, however, on the parameters for income and for distance to retail and number of retail alternatives for both services. This makes sense because we should expect consumers of different income levels to have different travel costs due to opportunity cost of time, geographic location and mean of transportation. Hence, not accounting for this dimension of the travel cost results in underestimating the differences in unobserved taste across income groups and the degree of substitution between the new

[12](Pakes et al. 2011) section 3.1.3 pages 34-38

[13]The value associated with a given coefficient γ is: $CS_\gamma = \frac{\gamma}{1-\alpha_1*10{,}000/hh\_income}$

online services and the consumers' offline vicinity. Not taking this heterogeneity into account also leads to biased estimates of the value of the two delivery services for the middle and high income groups. It overestimates the value of the Blue service for these groups, relative to the omitted lower income group, and underestimates the value of Green for the high income group. As previously discussed, these services have different distributions of users' income. And, if it's true that households of different income groups have different travel costs then, not taking heterogeneity in travel costs into account is going to affect the estimated value of these services potentially in different ways.

The parameter results show the different channels through which consumers benefit form a new retail alternative. An important dimension studied in this paper is how the distance to offline alternatives and variety of offline alternatives in the consumer's vicinity affects the value they attribute to a new online service. The travel cost is one channel that affects this value: the more distant the consumer is to brick-and-mortar retailers, the higher their cost to choose an offline retailer and the more attractive is the online service. With a travel cost of $\$0.55$/ mile and an average distance traveled to a grocery store of 7.97 miles, consumers incur on average an utility loss due to travel costs of approximately $\$4.38$ per shopping trip. The variety of alternatives within 1 and 5 miles also affects the benefits that consumers get from the online services. An additional retailer within 1 mile makes the Blue and the Green services less valuable by $\$0.36$ and $\$0.44$, respectively. Between 1 and 5 miles the effect for the Blue service is much smaller (a negative effect of $\$0.04$) and, the effect for the Green service is positive: an additional retailer between 1 and 5 miles increases the value of this service by $\$0.26$ per shopping trip. This is due to the fact that this service requires local stores to operate and, the more stores are located in close to a zip code the more partnerships the Green service will offer and the more value this service will generate to consumers.

In order to disentangle the effect from the Green service's increased quality due to proximity to partner stores and the substitution effect of offering the service in an area that already has a variety of brick-and-mortar options, in specifications (3) and (4) I add the number of partners offered by the Green service as a variable and the distance between the consumer and the closest store. New online services are more valuable to consumers who live further from the closest store (grocery, drug store or discount store). In the specification with ν_2, I find that the Blue and the Green services are $\$0.46$ and $\$0.34$ more valuable per shopping trip, respectively, per mile of distance between the consumer and the closest store. An additional partnership offered to the consumer makes the Green service worth $\$1.44$ more per shopping trip. This specification allows me to calculate the value associated with this complementarity between this service and its partners and discuss how it affects consumers differently due to their geographic living location. As shown in figure (7), zip codes with higher average income have on average more retailer partnerships offered through Green. Zip codes with an average income of up to $45K$ that are served by Green have on average 7.21 partners offering delivery whereas zip codes with average income of more than $70K$ have 10.96. This is a difference of 34% on the quality of the Green service across these two income groups due to differences in pre-existing availability of offline retail. Low income households then miss out on approximately $\$5.25$ per shopping trip of welfare relative to high income households due to complementarity between the Green service and the nearby offline retailers. Since users of delivery services make approximately 10.21 purchases per year, low income households could benefit over $\$50$/year more from the Green service if they lived in zip codes with an average income of more than $70K$. On the other hand, since low income households live at a further distance from stores they benefit more form online services through the substitution channel. On average, a low income zip code in the sample is on average 6.88 miles from the closest store whereas a a high income one is at 5.44 miles. Since each mile contributes $\$0.34$ per trip to the value of the Green service and $\$0.49$ to the value to of Blue, low income households can benefit up to 26.4% more per purchase from these services through this channel. An average low income zip code then benefits approximately up to $\$21.52$ per year from having access to a delivery service exclusively due to distance to brick-and-mortar stores (see table (15)).

Other demographic characteristics that matter for the value of convenience are age and gender (table (12)). Households where either the female or the male head are under 30 years old value online delivery between $\$1.66$ and $\$3.09$ more than households where one of the heads is older (depending on the service and the specification). Households of single females also value the services slightly more than other types of family: up to $\$0.54$ more for Blue and up to $\$0.79$ for Green per shopping trip. Another element that seems to matter for the relative value of these two services is what consumers buy. An expensive bundle, which is more likely to include more items than a inexpensive one (at least for groceries), adds more value to the Green service than it does to Blue.

The overall welfare value of the same-day delivery market is estimated by inferring the welfare loss from removing both Blue and Green firm from consumers' choice set. I multiply the value per trip of each consumer by their average number of purchases through Blue and Green services to get the yearly welfare values. The average welfare gain to consumers in this new market is approximately $\$120$/year using the parameters estimates from specification (4). When both services are offered and consumers are allowed to substitute between them, the incremental service generates a welfare gain of 27%. The average value to users is then approximately $\$170$/year. The average yearly consumer surplus is largely driven by wealthy consumers as they benefit the most per purchase but also because they shop more frequently through these new services, as shown in table (14a).

I use the model estimated to predict choices for a sample of households with a variety of demographic characteristics. I focus on differences in substitution patterns across income groups between the new services and offline alternatives. I look at predicted choices that result in either Blue or Green being the chosen retailers. Then, I remove these alternatives from consumer's choice set and predict choices again to identify the "second choice" of individuals according to their demographic characteristics and the retailing channel chosen. The goal of this exercise is to point out the mechanisms in the model that explain some of the regression analysis in section (IV). The comparison across tables (16a) and (16b) indicates that, for the lowest income group, the Blue service is a closer substitute for the grocery channel than Green is: 92% of time an individual in that group chooses Blue, the grocery channel is the second best offline option and, only 76% of the time this is the case when Green is chosen. The results also indicate that, even though Blue is a close substitute to groceries for the lowest income group, the middle and high income groups also use Blue as a substitute for drug store trips about 20% and 13% of the time, respectively.

The difference in travel costs across households plays a role in generating heterogeneity in the utility of offline alternatives across groups, given that the average distance to the closest store of a given retailer may vary with the household's income: see tables (6a) to (6c). Notably, the zip codes in the lowest income bracket have on average 0.41 and 0.38 standard deviations less grocery stores and drug stores per capita, respectively, than zip codes in the highest income bracket. The opposite is true for general merchandise stores: the low income zip codes tend to have more of those stores, relative to the two other income groups. Moreover, lower income households tend to live at a greater distance from retail stores and, also have less variety of retail partners when they have access to the Green service: see figure (7).

Table (17) shows the level of concentration of the business stealing of these two firms across other retailers. For predicted choices where Blue or Green were chosen, I present the percentage of the times that the top-ranked second choices occupied that position. The largest online loser is the second choice

33% of the times when Blue is the first choice. That same retailer is the second choice 35% of the time when Green is chosen. That same table also shows the largest offline losers by channel.

VIII. CONCLUSION

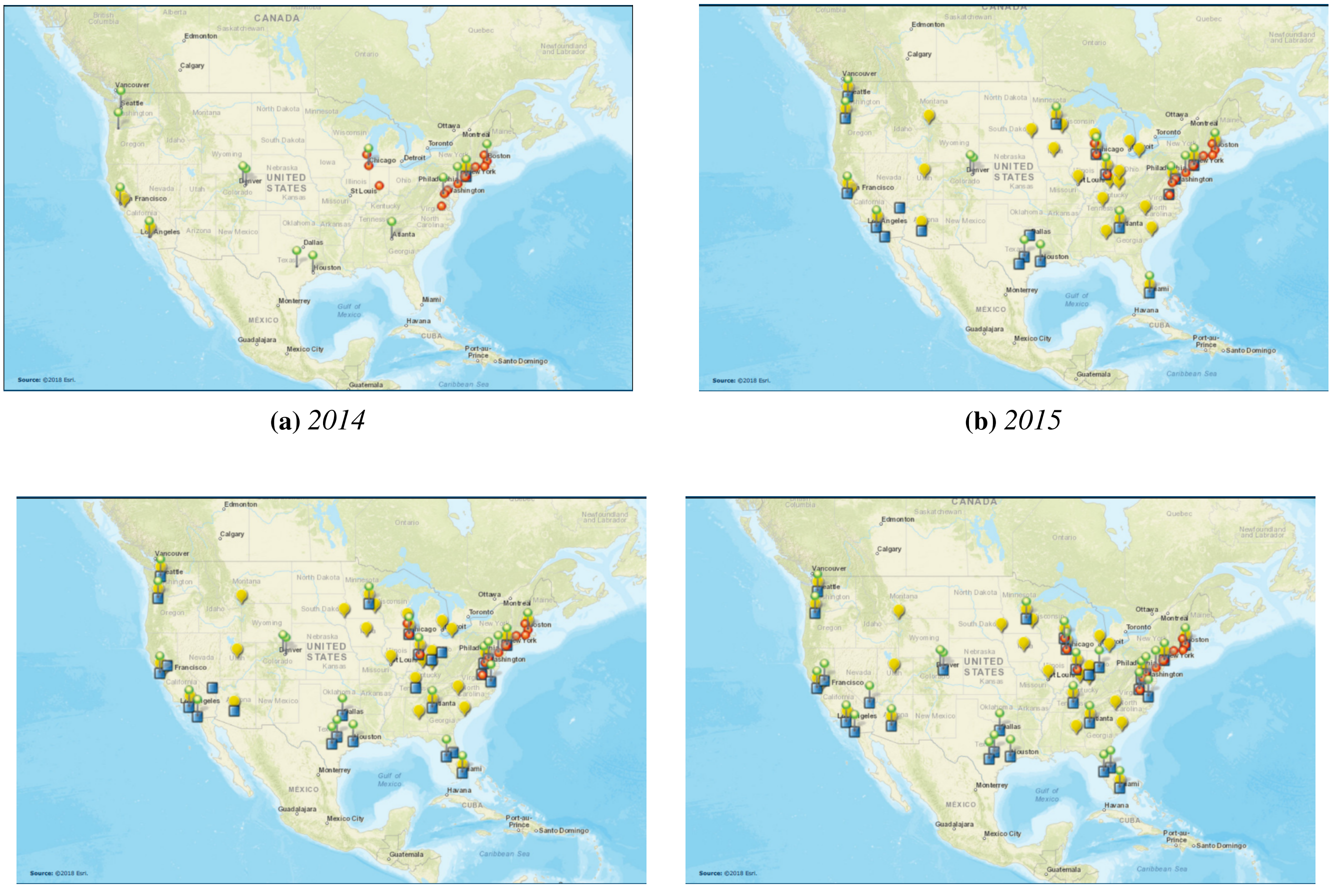
This paper assesses the welfare value of two same-day grocery delivery platforms. I estimate a Revealed Preference model where households with different demographic characteristics, different choice sets and different travel costs choose bundles and retailers. I use a modern estimation technique in order to overcome some of the common specification challenges present when modeling store choices and combine it with a new dataset that has unique time and geographic variation to single-out the effect of this new technology on households' shopping decisions. Moreover, by comparing two new online alternatives that are similar in their speed of delivery but differ in their relationship with offline retail, I am able to identify distinct effects that the expansion of e-commerce can have on both consumers and the local economy.

One of the key findings concerns the characteristics of the consumers that benefit the most from these innovations. High income consumers benefit more from the new technologies than any other demographic group. They benefit through a complementarity channel where the brick-and-mortar retailers near their homes increase the value of the online service (for Green only). A service that relies on the pre-existing supply of retail alternatives can generate large disparities between low and high income groups when discrepancies in access to retail already exists between these groups. This paper also includes demand features that help explain why households of different income levels resort to different retail channels by using rich information on distance to stores and heterogeneous travel costs.

Finally, this paper establishes some important facts about demand features that should be considered when studying e-commerce and its impact on the retail sector. Indeed, same-day grocery delivery is valuable to consumers (on average $120/year) and the convenience dimension of the online experience is an important determinant of retailer choice.

A. FIGURES AND TABLES

Figure 1: *National Roll-out of Grocery Delivery Services (2014-2017)*

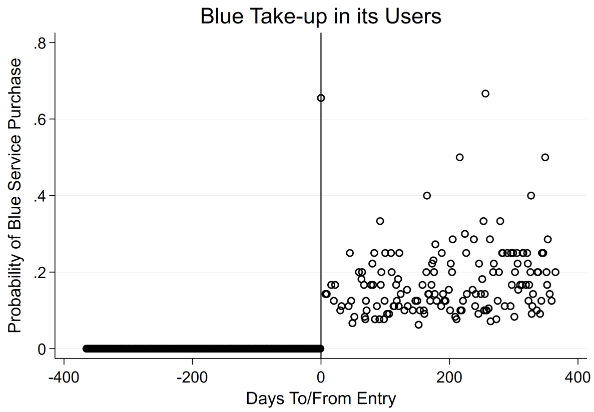


(a) *2014* **(b)** *2015*

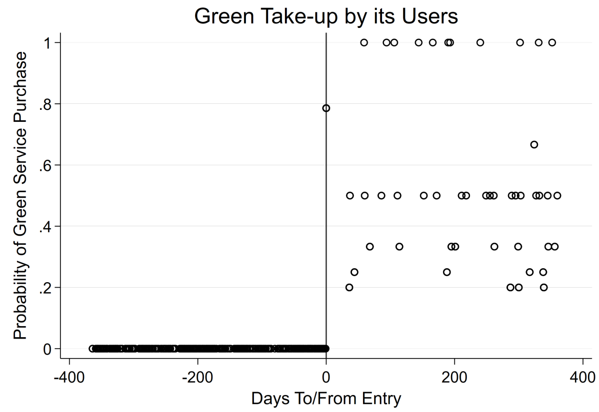
(c) *2016* **(d)** *2017*

Note: Each colored pin represents a different grocery delivery service. Blue firm is represented by blue squares and Green firm by green pins. Yellow and red pins represent two other large grocery delivery services.

Figure 2: *Services Take-up*



(a) *Blue Firm Take-up*



(b) *Green Firm Take-up*

Note: Frequency of Blue or Green service purchases by number of days from launch among all online transactions of Nielsen panelists that have used either service in the period of 2015-2016. Panelists making these transactions are spread across 27 metro areas where the launch of each service has occurred at a different date. Graphs show that the scraped arrival dates match the timing of when purchases start emerging in the Nielsen data.

Table 1: *Observations by Delivery Status*

(a) *Shopping Trips in Panel*

	Green Not Available	Green Available	Total
Blue Not Available	312,158	364,593	676,751
Blue Available	369,491	334,907	704,398
Total	681,649	699500	1,381,149

(b) *Households in Panel*

	Green Not Available	Green Available	Total
Blue Not Available	2,132	2,462	4,594
Blue Available	2,477	2,231	4,708
Total	4,609	4,693	9,302

(c) *Corresponding Zip Codes in Panel*

	Green Not Available	Green Available	Total
Blue Not Available	355	314	669
Blue Available	354	326	680
Total	709	640	1349

(d) *Sample Zip Codes Tested*

	Green Not Available	Green Available	Total
Blue Not Available	8,913	4,863	13,776
Blue Available	354	1,716	2,070
Total	9,267	6,579	15,846

(e) *Zip Codes Tested Mean Income*

	Green Not Available	Green Available	Total
Blue Not Available	84,033.76	83,927.38	83,971.76
Blue Available	73,044.17	88,048.86	82,683.82
Total	75,308.69	87,356.78	82,918.19

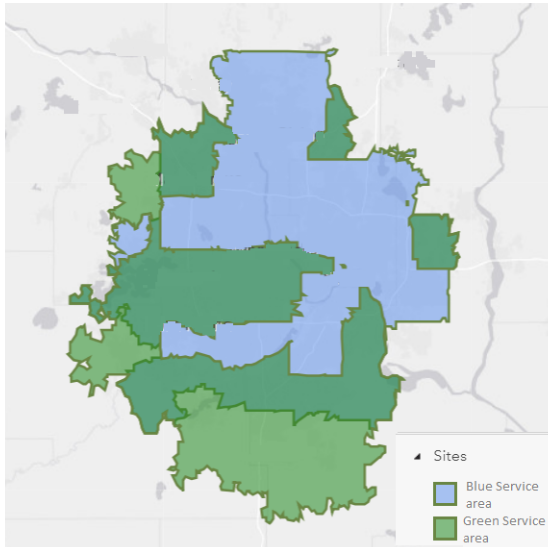
Note: Table includes number of observed shopping trips to the 4 channels of interest (Grocery, Discount Store, Drug Store and Online Shopping) during 2015-2016 for panelists in the 27 metro areas where there are launches of either Blue or Green (or both) in one of these two years. This includes trips before and after the launches. The total number of trips will correspond to the total number of observations in tables (7)-(9) across all three income groups. The corresponding number of households making those trips and zip codes are also presented. The last two tables contain all zip codes with information on availability status scraped from services' website. This larger sample of zip codes is used to match income data from the 2012-2016 American Community Survey 5-Year Estimates (ACS) and supplemetary information on the number of retail establishments by NAICS code come from the Zip Codes Business Patterns (ZBP) 2015.

Table 2: *27 Metro Areas Where Panelists Who Are Same-day Delivery Users Are Located*

Metro Area	2016	2015
Atlanta	x	x
Baltimore	x	x
Boston	x	x
Chicago	x	x
Cincinnati	x	
Columbus	x	
Dallas	x	x
Denver	x	x
Houston	x	x
Indianapolis	x	x
Las Vegas	x	x
Los Angeles	x	x
Miami	x	x
Minneapolis-St. Paul	x	x
Nashville	x	
New York	x	x
Orlando	x	
Phoenix	x	x
Portland	x	x
Raleigh-Durham	x	
Richmond	x	x
Sacramento	x	
San Antonio	x	x
San Diego	x	x
San Francisco	x	x
Seattle	x	x
Tampa	x	
Washington DC	x	x

Note: Table displays metro areas associated with panelists that use either service (Blue or Green) at some point in 2015-2016. An "x" for a metro area/year pair means that there are shopping trip observations for panelists that use a same-day delivery service during that year in that location. I consider urban and suburban divisions of the same markets as a part of the same metro area.

Figure 3: *Delivery Radius By Service*



Note: Example of delivery radius for a metro area in the sample at the beginning of the sample period. Zip codes in blue are uniquely served by Blue firm, zip codes in light green are uniquely served by Green firm and the dark green area corresponds to zip codes served by both services.

Table 3: *Shopping Trip Characteristics By Retail Channel*

(a) *Cost of Bundles Bought ($)*

	Mean Value Spent Per Trip	Std. Dev.
Discount Store	59.20	67.22
Drug Store	29.52	48.79
Grocery	45.82	52.03
Online Shopping	68.41	97.16

(b) *Distances Traveled (miles)*

	Min. Distance Traveled in miles	Std. Dev.
Discount Store	8.68	7.54
Drug Store	9.50	7.38
Grocery	7.97	6.75

(c) *Number of Product UPCs*

	Average Nb. of UPCs/Retailer	Std. Dev.
Discount Store	49,694.25	32,123.79
Drug Store	7,764.16	5,098.56
Grocery	22,625.52	17,064.89
Online Shopping	1,317.12	1,220.10

Note: Each observation is a shopping trip to the relevant channels in the data during 2015-2016 in the 27 metro areas used. Table (3a) presents the mean dollar value of the bundles purchased in trips associated with each channel. Table (3b) presents the mean distance between panelists and the closest store of each channel. Table (3c) presents the average number of UPC codes bought in stores owned by retailers associated with each channel.

Table 4: *Characteristics of Purchased Bundles Across Income Groups*

(a) *Differences in Grocery Baskets Across Income Groups in Trips to Same Retailer*

Income Bracket	Nb. of Fresh Produce in Basket	std. dev.
$[0, 45, 000)$	1.05	.75
$[45, 000 - 70, 000)$	1.32	1.14
$\geq 70, 000$	1.51	1.09

(b) *Differences in Grocery Baskets Across Income Groups in Trips to Green Firm*

Income Bracket	Nb. of Fresh Produce in Basket	Std. dev.
$[0 - 45, 000)$	1.41	1.06
$[45, 000 - 70, 000)$	1.37	1.21
$\geq 70, 000$	1.60	1.20

Note: Table (4a) presents the average and standard deviation of the number of fresh produce items in bundles purchased by households in each income group. For each retailer visited by multiple panelists of each income group, means in table (4a) are calculated across panelists that visit the same retailer. Table (4b) shows means and standard deviations for the number of fresh produce in the basket purchased for panelists that use the Green service across income groups.

Table 5: *Demographic Characteristics of Panelists*

	Sample	Blue Users	Green Users
Under 30 years old	39.44	44.22	55.84
Under 50 years old	63.21	55.20	72.73
Single Female	26.47	31.79	42.86
Single Male	9.96	12.14	11.69
White	81.60	84.10	70.13
Black	10.46	8.38	20.78
Asian	3.16	3.17	1.30
Other (race)	4.77	4.05	7.79
Hispanic	6.46	8.96	10.39
Children Under 18	23.90	11.85	18.18
Active Internet	94.94	97.40	97.40
Highest Degree in Household:			
Grade School	0.15	0.29	0.00
Some High School	0.98	0.16	0.00
Graduated High School	18.18	17.63	9.09
Some College	28.79	31.21	29.87
Graduated College	34.00	35.55	31.17
Post College Grad	17.90	14.16	29.87
Income $<$ 45K	39.34	42.20	31.17
Income [45K, 70K)	24.89	27.75	32.47
Income $\geq$ 70K	35.77	30.06	36.36

Note: All variables are dummies. Hence, the table shows the proportion panelists with each demographic characteristic within each subgroup. The first column shows the proportions for the entire set of Nielsen panelists in 2015-2016. Single female and male households are households with no male head of household and no female head of household, respectively.

Table 6: *Availability of Stores by Channel and Income Group*

(a) *Number of Grocery Stores Per Capita in Zip Codes of Different Income Levels*

Income Group	Zip Code Mean	Std. dev.
Income $<$ 45K	.26	1.86
Income [45K - 70K)	.28	1.89
Income $>$ 70K	.96	3.03

(b) *Number of Drug Stores in Zip Codes Per Capita of Different Income Levels*

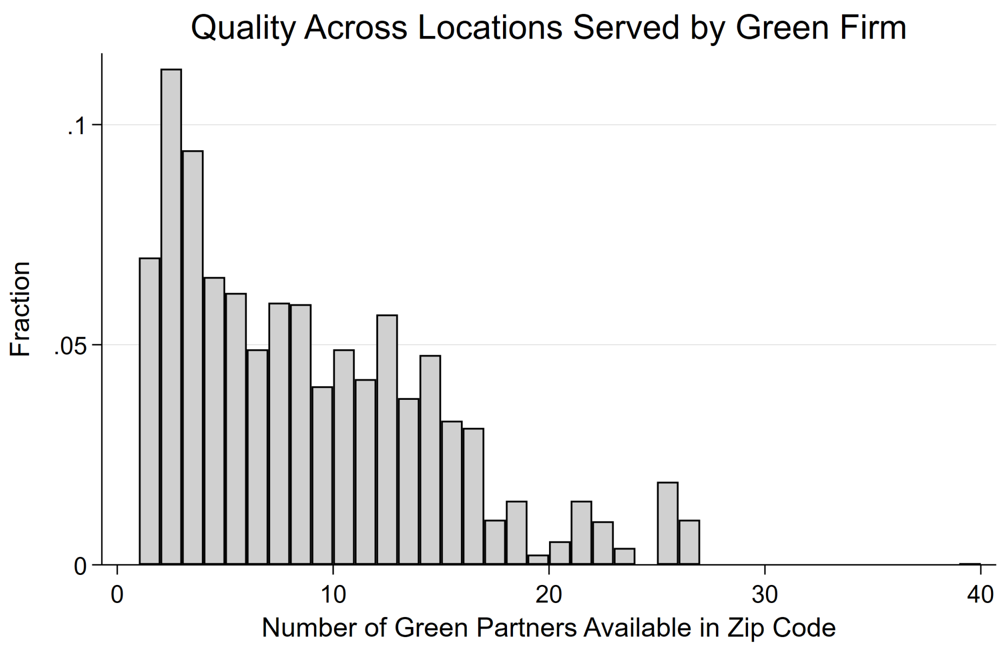
Income Group	Zip Code Mean	Std. dev.
Income $<$ 45K	.076	.729
Income [45K - 70K)	.070	.551
Income $>$ 70K	.376	1.471

(c) *Number of General Merchandise Stores Per Capita in Zip Codes of Different Income Levels*

Income Group	Zip Code Mean	Std. dev.
Income $<$ 45K	4.20	4.63
Income [45K - 70K)	3.28	3.62
Income $>$ 70K	2.36	2.91

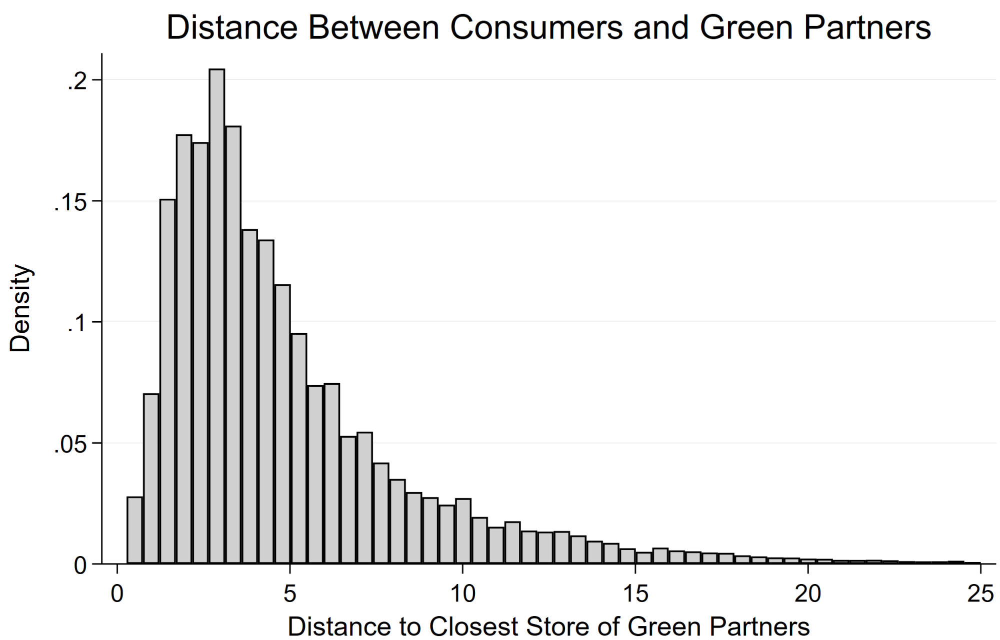
Note: Average income and population by zip code comes from the 2012-2016 American Community Survey 5-Year Estimates (ACS) and the number of retail establishments by NAICS code come from the Zip Codes Business Patterns (ZBP) 2015.

Figure 4: *Distribution of Partners Available on Green Platform*



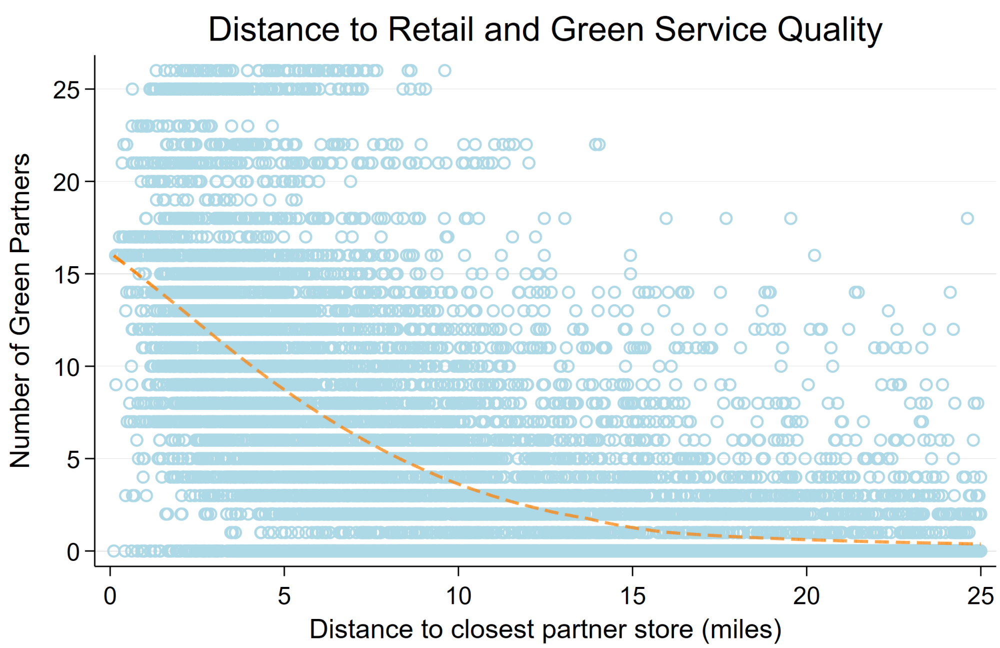
Note: An observation is a zip code and the the number of retailers that fulfill deliveries to that zip code though Green's platform.

Figure 5: *Distribution of Minimum Distance Between Consumers and Green Partner Stores*



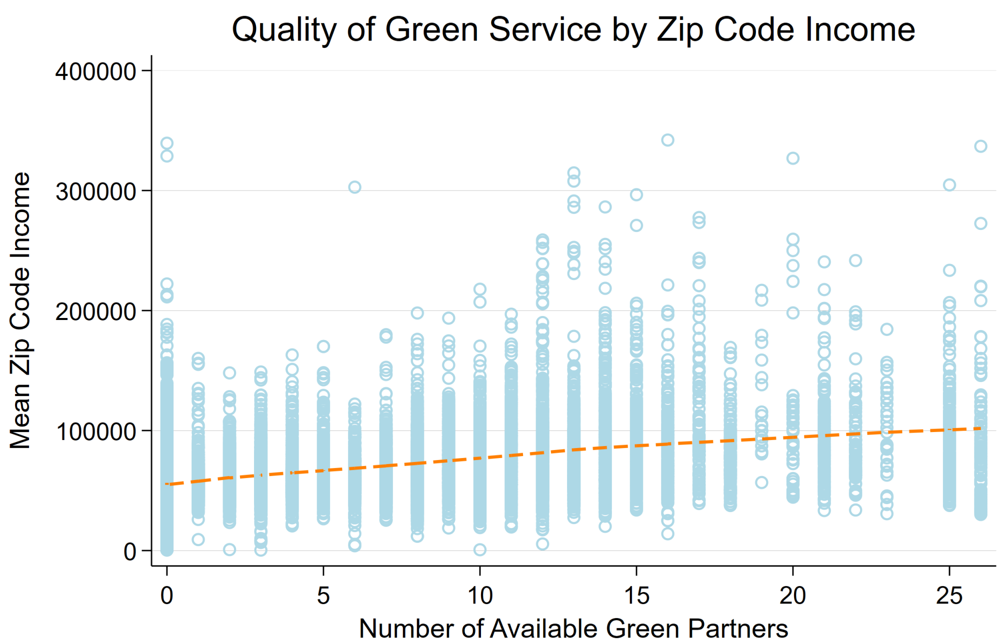
Note: An observation is a zip code served by the Green firm and the distance from that zip code's centroid to the closest store of a retailer that is a partner of Green firm.

Figure 6: *Distance to Stores and Number of Partners Available on Green's Platform*



Note: An observation is a zip code served by the Green firm, a distance from that zip code's centroid to the closest store of a retailer that is a partner of Green firm and the number of retailers that fulfill deliveries to that zip code though Green's platform. This graph displays the lowess regression aproximation of the relationship between distance from partner stores and number of partners available.

Figure 7: *Distance to Stores and Zip Code Income*



Note: An observation is the mean income of households in each U.S. zip code and the number of partners offered by the Green service in that zip code. The mean household income by zip code comes from the 2012-2016 American Community Survey 5-Year Estimates (ACS). This graph displays the lowess regression approximation of the relationship between the number of partners offered and the zip code mean household income.

Table 7: *Effect of Blue and Green Service Launches on Probability of Grocery Store Purchase by Users of Each Service*

VARIABLES	(OLS) Income < 45K	(OLS) Income [45K - 70K)	(OLS) Income > 70K
Green Available * Green User	-0.106***	-0.121***	-0.330***
	(0.0177)	(0.0402)	(0.0227)
Blue Available * Blue User	-0.352***	-0.114***	-0.0271*
	(0.0310)	(0.0111)	(0.0140)
Constant	0.465***	0.535***	0.552***
	(0.0187)	(0.00710)	(0.00737)
Household FE	YES	YES	YES
Month FE	YES	YES	YES
Observations	96,475	651,726	632,948
R-squared	0.035	0.021	0.019

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

Note: Observations include all trips to grocery stores, discount store and drug stores made by households in the 27 metro areas that contain Blue and Green service users in 2015-2016. For each trip, the dependent variable takes value 1 if the store visited belong to the Grocery channel. Coefficients represent the change in the probability of a same-day delivery service user making a trip to a grocery store after the this new service become available in their zip code.

Table 8: *Effect of Blue and Green Service Launches on Probability of Discount Store Purchase by Users of Each Service*

VARIABLES	(OLS) Income $<$ 45K	(OLS) Income [45K - 70K)	(OLS) Income $>$ 70K
Green Available * Green User	0.0306	0.0787**	-0.0277
	(0.0319)	(0.0342)	(0.0190)
Blue Available * Blue User	-0.0759***	-0.107***	-0.106***
	(0.0253)	(0.00944)	(0.0117)
Constant	0.156***	0.158***	0.154***
	(0.0152)	(0.00603)	(0.00617)
Household FE	YES	YES	YES
Month FE	YES	YES	YES
Observations	96,475	651,726	632,948
R-squared	0.100	0.077	0.071

Standard errors in parentheses

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

Note: Observations include all trips to grocery stores, discount store and drug stores made by households in the 27 metro areas that contain Blue and Green service users in 2015-2016. For each trip, the dependent variable takes value 1 if the store visited belong to the Discount Store channel. Coefficients represent the change in the probability of a same-day delivery service user making a trip to a discount store after the this new service become available in their zip code.

Table 9: *Effect of Blue and Green Service Launches on Probability of Drug Store Purchase by Users of Each Service*

VARIABLES	(OLS) Income < 45K	(OLS) Income [45K - 70K)	(OLS) Income > 70K
Green Available * Green User	0.0248	0.000243	0.0239*
	(0.0235)	(0.0250)	(0.0141)
Blue Available * Blue User	0.00583*	-0.0421***	-0.0173**
	(0.00352)	(0.00690)	(0.00871)
Constant	0.0970***	0.0664***	0.0609***
	(0.0126)	(0.00441)	(0.00457)
Household FE	YES	YES	YES
Month FE	YES	YES	YES
Observations	96,475	651,726	632,948
R-squared	0.081	0.066	0.057

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

Note: Observations include all trips to grocery stores, discount store and drug stores made by households in the 27 metro areas that contain Blue and Green service users in 2015-2016. For each trip, the dependent variable takes value 1 if the store visited belong to the Drug Store channel. Coefficients represent the change in the probability of a same-day delivery service user making a trip to a drug store after the this new service become available in their zip code.

Table 10: *Effect of Offline Retail Availability on Probability of Green Service Usage*

VARIABLES	(OLS) Green	(OLS) Green	(OLS) Green
Distance to Closest Green Partner Store (miles)	-0.000384	0.00215***	0.00170***
	(0.000513)	(0.000556)	(0.000556)
Number of Green Partners Available		0.00334***	0.00329***
		(0.000306)	(0.000304)
Number of Stores within 1 mile			-0.00370***
			(0.000498)
Constant	0.0155***	-0.0271***	0.0365***
	(0.00309)	(0.00495)	(0.00987)
Observations	3,890	3,890	3,890
R-squared	0.000	0.030	0.043

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

Note: Observations coincide with the sample of trips used in the estimation of the structural model in section (V). Trips are a random sample of grocery, discount store and drug store purchases as well as online purchases from the Green and Blue services made by households in the 27 metro areas that contain Blue and Green service users in 2015-2016. For each trip, the dependent variable takes value 1 if the retailer corresponding to that purchase is the Green service. Coefficients represent the correlation of each variable with the probability of a consumer using that service at any point in time.

Table 11: *Effect of Offline Retail Availability on Probability of Blue Service Usage*

VARIABLES	(OLS) Blue	(OLS) Blue	(OLS) Blue
Distance to Closest Green Partner Store (miles)	-0.00106	-0.000702	-0.000997
	(0.000840)	(0.000880)	(0.000881)
Distance to Closest Store (miles)	0.00672***	0.00751***	0.00684***
	(0.00165)	(0.00174)	(0.00175)
Number of Green Partners Available		0.000685	0.000585
		(0.000495)	(0.000495)
Number of Stores within 1 mile			-0.00318***
			(0.000769)
Constant	0.00480	-0.00694	0.0510***
	(0.00780)	(0.0115)	(0.0181)
Observations	3,890	3,890	3,890
R-squared	0.004	0.005	0.009

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

Note: Observations coincide with the sample of trips used in the estimation of the structural model in section (V). Trips are a random sample of grocery, discount store and drug store purchases as well as online purchases from the Green and Blue services made by households in the 27 metro areas that contain Blue and Green service users in 2015-2016. For each trip, the dependent variable takes value 1 if the retailer corresponding to that purchase is the Blue service. Coefficients represent the correlation of each variable with the probability of a consumer using that service at any point in time.

Table 12: *Revealed Preference Estimates (in \$): Demographics*

	(1)	(2)	(3)	(4)
Blue * Under 30	0.038	2.51	2.39	3.09
	[0.037, 0.038]	[2.46, 2.53]	[2.36, 2.44]	[3.04, 3.14]
Blue * Income [45K - 70K)	12.26	6.81	7.36	10.85
	[12.04, 12.33]	[6.66, 6.86]	[7.24, 7.47]	[10.65, 10.98]
Blue * Income > 70K	19.98	9.85	10.51	7.84
	[19.66, 20.30]	[9.23,10.28]	[10.34, 10.68]	[7.64, 7.94]
Blue * Single Female	0.162	0.242	0.228	0.543
	[0.159,0.165]	[0.237, 0.242]	[0.225, 0.232]	[0.532, 0.551]
Blue * Bundle Value	0.083	0.053	0.0588	0.0616
	[0.082, 0.084]	[0.052, 0.054]	[0.0578, 0.0597]	[0.0602, 0.0625]
Blue * Retailers < 1 mile	-0.181	-0.355		
	[-0.185, -0.179]	[-0.363, -0.353]		
Blue * Retailers < 5 miles	-0.041	-0.044		
	[-0.040, -0.041]	[-0.046, -0.044]		
Blue * Nb Green Partners			-1.014	-0.799
			[-1.030, -0.997]	[-0.817, -0.789]
Blue * Closest Store (miles)			0.487	0.461
			[0.479, 0.495]	[0.452, 0.467]
Green * Under 30	3.08	1.75	2.15	1.66
	[3.03, 3.13]	[1.69, 1.77]	[2.12, 2.19]	[1.62 1.69]
Green * Income [45K - 70K)	0.085	0.00140	0.00132	0.00081
	[0.084, 0.086]	[0.00136, 0.00141]	[0.00130,0.00134]	[0.00079, 0.00082]
Green * Income > 70K	1.51	8.59	9.10	13.25
	[1.49, 1.59]	[8.40, 8.67]	[8.96, 9.25]	[12.97, 13.40]
Green * Single Female	0.59	0.76	0.79	0.36
	[0.58,0.60]	[0.75, 0.79]	[0.78, 0.80]	[0.35, 0.36]
Green * Bundle Value	0.097	0.199	0.227	0.478
	[0.095, 0.098]	[0.194, 0.201]	[0.223, 0.230]	[0.469, 0.485]
Green * Retailers < 1 mile	-0.979	-0.444		
	[-0.995, -0.963]	[-0.443, -0.445]		
Green * Retailers < 5 miles	0.335	0.26		
	[0.329, 0.340]	[0.24, 0.27]		
Green * Nb Green Partners			1.029	1.428
			[1.013, 1.046]	[1.400, 1.444]
Green * Closest Store (miles)			0.504	0.342
			[0.496, 0.512]	[0.335, 0.346]
Retailer Fixed-effects	YES	YES	YES	YES
ν_2	NO	YES	NO	YES

Note: Estimates based on a random sample of 3,890 visits across all 4 channels: Grocery, Discount Store, Drug Store and Online Shopping. Both specification include 35 retailer chain dummies (fixed-effects). Confidence intervals of 95% from bootstrapping of approximated outer distribution.

Table 13: *Revealed Preference Estimates (in $)*

	(1)	(2)	(3)	(4)
Income * Expenditure (10K)	0.47	0.55	0.572	0.569
	[0.46,0.48]	[0.42, 0.56]	[0.563, 0.581]	[0.558, 0.568]
Assortment (+1K UPCs)	1.09	0.89	1.40	0.95
	[1.07, 1.11]	[0.87, 0.90]	[1.38, 1.43]	[0.93, 0.96]
Travel Cost ($/mile)	0.45	0.55	0.56	0.55
	[0.44,0.46]	[0.54, 0.56]	[0.55, 0.57]	[0.55, 0.56]
Retailer Fixed-effects	YES	YES	YES	YES
ν_2	NO	YES	NO	YES

Note: Estimates based on a random sample of 3,890 visits across all 4 channels: Grocery, Discount Store, Drug Store and Online Shopping. Both specification include 35 retailer chain dummies (fixed-effects). Confidence intervals of 95% from bootstrapping of approximated outer distribution.

Table 14: *Value of Online Services by Income Level*

(a) *Number of Purchases Using Online Delivery/ Year*

	Blue or Green	All Online retailers
Income > 70K	9.26	25.59
Income [45K, 70K)	7.61	19.94
Income < 45K	6.81	19.13

(b) *Consumer Surplus by Income Group ($): Blue*

	Surplus/ Purchase	Surplus/ Year
Income > 70K	21.36	197.79
Income [45K, 70K)	13.64	103.80
Income < 45K	4.94	33.64
Weighted Average	12.85	131.20

(c) *Consumer Surplus by Income Group ($): Green*

	Surplus/ Purchase	Surplus/ Year
Income > 70K	13.94	129.08
Income [45K, 70K)	4.77	36.30
Income < 45K	1.41	9.60
Weighted Average	9.85	95.81

Note: The first table shows the household average number of purchases per year by income group for the new online delivery services and for any online purchase. The second and third tables show the consumer surplus induced by the new services estimated by the model. The results presented make use of the estimates in column (4) table (12) and table (13). The counterfactual performed removes both services from consumers' choice set. The annual values make use of each consumer's average yearly online delivery purchases. The weighted average is a mean across households that the model predicts will make purchases through each new service, given a bundle of products. Therefore, it places a larger weight on more frequent users and users with larger surplus according to the model.

Table 15: *Value of Complementarity and Substitution Components*

(a) *Green Firm: Dollar Value per Purchase*

	Complementarity ($)	Substitution ($)
Income > 70K	15.67	1.85
Income [45K, 70K)	9.27	2.83
Income < 45K	10.24	2.34

(b) *Green Firm: Dollar Value per Year*

	Complementarity ($)	Substitution ($)
Income > 70K	145.10	17.13
Income [45K, 70K)	70.54	21.54
Income < 45K	69.73	15.94

(c) *Blue Firm: Dollar Value per Purchase*

	Complementarity ($)	Substitution ($)
Income > 70K	0	2.50
Income [45K, 70K)	0	3.83
Income < 45K	0	3.16

(d) *Blue Firm: Dollar Value per Year*

	Complementarity ($)	Substitution ($)
Income > 70K	0	23.15
Income [45K, 70K)	0	29.15
Income < 45K	0	21.52

Note: This table shows the dollar value to consumers associated exclusively with the complementarity and substitution channels relative to offline retail in the vicinity of their homes. The results presented make use of the estimates in column (4) table (12) and table (13). The annual values make use of each consumer's average yearly online delivery purchases.

Table 16: *What is the Offline 'Second Choice' When Consumers Choose Same-day Delivery?*

(a) *Blue Service*

Channel of Second Choice	Income < 45K	Income [45K - 70K)	Income > 70K
Discount Store	X	1.3%	1.94%
Drug Store	8.16%	19.48%	12.62%
Grocery Store	91.84%	79.22%	85.44%

(b) *Green Service*

Channel of Second Choice	Income < 45K	Income [45K - 70K)	Income > 70K
Discount Store	22.22%	9.82%	7.00%
Drug Store	1.85%	9.38%	9.73%
Grocery Store	75.93%	80.80%	83.27%

Note: Table shows substitution patterns between the two delivery services and 3 offline channels. The share of choices associated with each channel are presented when the two same-day delivery services are removed from the choice set and retailer choices implied by the model are from one of the 3 offline channels.

Table 17: *Biggest Losers: Top 'Second Choice' Retailers*

Second Choice Retailers	Blue as Choice	Green as Choice
Largest Online Loser	33%	35%
Largest Grocery Loser	7.22%	2.92%
Largest Discount Loser	0.31 %	3.23%
Largest Drug Store Loser	3.35%	2.92%

Note: Table shows substitution patterns between the two delivery services and retailers from 3 offline channels as well as the online channel. The share of choices associated with each channel are presented when the two same-day delivery services are removed from the choice set.

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