Entry Timing and the Welfare Effect of Mergers in the Same-day Grocery Delivery Market

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Abstract

This paper proposes a framework to measure the welfare created by an innovation when consumer lock-in shapes firms' entry timing. I apply it to the evaluation of actual and potential mergers in the grocery delivery market to show how competition benefits consumers by accelerating entry of a new service across geographical markets. The two largest delivery platforms in the U.S. both offer subscriptions and, in the data, consumers that have access to both services rarely switch between them. I find that, switching costs significantly affect platform choice, generating consumer lock-in. Firms then have the incentive to chase a first-mover advantage, entering markets early to build a customer base. My model is a dynamic game between two platforms. Entry timing affects the firms' customer base growth, governed by the demand model. I find that entry costs fall over time for both firms, leading to significant costs of early entry. The first counterfactual analyses an actual merger between one of the platforms and a brick-and-mortar grocery chain which reduced this platform's entry cost across many markets. I find that, due to lock-in, it raised the stakes of early entry for the competitor, accelerating entry across new markets by more than two years. The second is a potential merger between the two platforms, resulting in a monopoly. I show the monopolist delays entry significantly and, due to lock-in, has an incentive to raise prices in the future. My welfare analysis of these mergers shows that strategic competition plays an important role in generating benefits to consumers through entry timing.

Keywords: Antitrust, Digital Platform Competition, Dynamic Oligopoly, First-Mover Advantage, Switching Costs

*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. I would like to express my appreciation to my committee - Amil Petrin, Thomas Holmes and Joel Waldfogel - for their valuable advice and support. For their helpful comments and suggestions, I thank Marcos Frazao, as well as seminar participants of the University of Minnesota Applied Microeconomics Workshop. Finally, I thank the Graduate School at University of Minnesota for the financial support through the Doctoral Dissertation Fellowship.

I. INTRODUCTION

The introduction of an innovation often occurs gradually, spreading geographically as the firm establishes operations in each location. Moreover, new product entry begets a strategic response form competitors. In particular, when firms compete to introduce versions of the new product and believe the first entrant benefits from some advantage, this strategic response involves entry timing. In this paper, I propose an empirical framework to measure the welfare effect of a new service when consumer lock-in shapes entry timing. I apply it to the evaluation of a merger that reduced a firm's entry cost and study how the strategic response of a competitor benefited consumers by accelerating the spread of the new service across geographical markets.

This paper contributes to the literature on the role of consumer inertia in competition. Even though there is a body of literature relating switching costs to price competition - (Rosenthal 1982), (MacKay and Remer 2019), (Bagwell, Ramey, and Spulber 1997), (Cabral 2012)[1] - much less is known about the implications of switching costs for entry decisions. This literature, to the best of my knowledge, is vastly theoretical: (Klemperer 1988), (Farrell and Shapiro 1988), (Klemperer 1995), (Farrell and Klemperer 2007), (Klemperer 1987) and (Schmidt 2010). And, although switching costs are theoretically deemed relevant for preserving advantages to early movers - (Lieberman and Montgomery 1988), (Shapiro and Varian 2000), (Amit and Zott 2001) - measurement of this advantage is also sparse (Gómez and Maícas 2011). The goal of this paper is not to argue that first-movers are able to sustain significant advantages over competitors in the presence of switching costs. Rather, I measure the role of switching costs in shaping entry strategies in a nascent market and the implications of this mechanism for consumer welfare.

This paper also relates to the empirical literature measuring the importance of entry timing to firm decisions in strategic settings. Although there is a vast theoretical work on this topic since the early technology diffusion literature (Reinganum 1981a), (Reinganum 1981b) and (Fudenberg and Tirole 1985), the empirical literature is much sparser due to the difficulty to single-out the motive driving timing from other sources of strategic behavior, as highlighted by the empirical literature on spatial preemption - (Schmidt-Dengler 2006), (Igami and Yang 2016) (Zheng 2016). I study the incentive to build a customer base which can indirectly form an entry barrier to later entrants. Hence, my approach relies on the demand

[1] For surveys, see: (Cabral 2016) and (Miguel Villas-Boas 2015)

model. I model the mechanism driving consumers' inertia and estimate the cost of switching between delivery platforms. Then, I model firm decisions as a dynamic entry game in which consumers' transition across platforms, induced by the estimated demand model, governs the law of motion of firm revenues. Firms then compete in continuous time across independent markets in a similar fashion to (Arcidiacono et al. 2016).

To estimate the demand model, I build on (Katz 2007)'s store choice model. I extend it to a dynamic setting where, in addition to choosing bundles of products and retailers, consumers also pay a sunk cost to subscribe to memberships that augment their choice set of online retail alternatives. In addition to the revealed preference relations used in (Katz 2007) which identify utility parameters, I estimate costs associated with subscriptions (fees and switching costs) using a second set of moments. These moments come from a set of revealed preference conditions which compare the utility of maintaining the consumer's subscription choice - inferred from their retail choices - to the utility of switching. To address the fact that this second set of moments carry unknown continuation values, I use rationality constraints and conditional choice probabilities to impose bounds on these values. These constraints impose rational switching behavior under each combination of state and choice and identify bounds on differences in continuation values across subscriptions that only depend on model parameters. I find that switching costs significantly affect consumer platform use. In the absence of switching costs, consumers would alternate between platforms between purchases ten times more often.

To study competition between same-day grocery delivery platforms, I use data on their geographical roll-out since they were each first launched. Two firms stand out in this market both due to the fact that they have polar opposite cost structures and because they are by far the largest firms in terms of U.S. population coverage (figure IV). These firms compete in many markets across the country (table III) and their entry patterns reflect their strategic considerations relative to the other. For data confidentiality reasons, I do not refer to these firms by their name. Instead, I use names that reference their different business models. *Big Tech* is the first firm: a traditional online retailer starting new logistical operations dedicated to same-day delivery and sourcing products from its own fulfillment centers. *Grocer Partner* is the second: an independent two-sided platform with massive geographic coverage and sourcing products from its grocery store partners[2].

[2] In 2017, this firm's service was available to 70% of the U.S. population. This is calculated directly using the availability

There is a recent increase in antitrust concern regarding mergers involving digital platforms and technology companies in general: (Zingales and Lancieri 2019), (Scott-Morton et al. 2019), (Khan 2017), (Shelanski 2013). Mergers have been widely used by digital platforms as a form of acquiring other technologies and shifting business to new markets (Cabral 2020). In the online grocery market specifically, competition between players addressed in this paper has been marked by an important event. In 2017, *Big Tech* acquires a large brick-and-mortar grocery chain, generating antitrust attention. On the one hand, I show evidence that this merger served the purpose of reducing entry costs for *Big Tech* across many geographical markets. Competition on entry timing with a rival with low entry costs then played a role in accelerating entry across new markets, giving consumers access to new delivery technologies sooner than they otherwise would. On the other hand, I also show that, while this merger contributed to the spread of the new product across many markets, a merger between the two platforms would do the opposite. Hence, this paper tries to contribute to this policy issue by providing an empirical framework to evaluate the welfare impact of mergers through its effect on the timing of introduction an innovation.

I study two types of mergers. The first is a retrospective analysis of this recent acquisition. I find that, had the acquisition not happened, both firms would have entered new markets over 2 years later. The combined costs associated with the two firms' earlier entry due to the acquisition amount to a loss of $624 M in producer surplus. However, consumer benefits across markets that were served earlier due to this merger are larger, representing a total welfare gain of $846 M. Additionally, the fact that this merger allowed *Big Tech* to enter multiple markets earlier provides an explanation for the premium paid for the acquisition[3]. Moreover, until this merger occurred, this retail chain was *Grocer Partner*'s largest partner, giving it access to approximately 23 million consumers[4]. This supports the fact that *Grocer Partner* anticipated how the acquisition would affect its ability to serve certain markets and reacted through earlier entry.

The second is a counterfactual that simulates a potential horizontal merger between the two largest grocery delivery platforms in the U.S.. I find that this merger would have very different consequences for competition and, as a result, for consumer welfare. My estimates show that, due to the lack of significant competitive threat, the monopolist would not have an incentive to serve markets early. Specifically, the

by zip code scraped from their website and Census data on population by zip code.

[3]https://mercercapital.com/financialreportingblog/amazon-whole-foods-and-value-implications/

[4]Combined population of the zip codes that had access to delivery from these stores through *Grocer Partner*.

monopolist would take over 6 years longer, on average, to enter the same markets the two largest platforms entered during 2012-2017 with competition. This shows the role of competition in the diffusion of a new product. I also show that consumer losses due to delayed entry by the monopolist in this market are larger than cost savings from this merger. Indeed, the monopolist would incur smaller costs of early entry, as it would have an incentive to wait for entry costs from the technology to be reduced. Moreover, the monopolist would be able to choose the most cost-efficient business model in each market and demand density would contribute to returns to scale. In both cases, the focus is on entry timing and firms do not choose prices in the model. For this reason, the merger analysis is limited as does not capture changes in price setting incentives. However, I use the demand model to show how consumers' substitution patterns as response to price changes shed light into whether a hypothetical monopolist would have the incentive to raise prices. I find evidence that competition is important to keep prices low, specially if the monopolist's business model relies on economies of scale.

Section (II) describes the data and details about the industry. In section (III), I present the demand model. In section (IV), I present the entry game followed by estimation results (V), counterfactuals (VI) and the conclusion (VII).

II. Data and Motivating Evidence

i. Data

The first data source used in this paper is the Nielsen Consumer Panel Dataset (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[5]. 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 (V) shows an example of the resulting delivery coverage by zip code for a metro area in the sample in 2015. The zip codes in are exclusively served by *Big Tech*, the ones in light green are exclusively served by *Grocer Partner* 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, to estimate demand, I work with 27 metro areas that include 680 zip codes served by *Big Tech* firm, corresponding to 4,708 households in the Homescan and, 640 zip codes served by the *Grocer Partner* 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 (III) includes all purchases from retailers *Big Tech* and *Grocer Partner* 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 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

[5]The *Grocer Partner* 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.

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.

In the following section (ii) , I show evidence that consumer choices are motivated by subscription timing and of the inertia associated with it. I then show evidence in section (iii) of the firms' strategic interaction through entry timing.

II. CONSUMER LOCK-IN

Table I shows the frequency of switching occurrences across platforms where an observation is a purchase. Table II shows the number of days after the first purchase using one of the two services it takes a switcher to switch. This table shows that the first time a consumer uses either service is likely to be when they first subscribe to that service as switching, if it occurs, happens around the expiration date of a monthly or yearly subscription. Switching rates measured in each of these two manners are quite low, consistent with other sources of data[6].

In order to describe where the variation identifying of switching costs in the demand model comes from, in figure I I show how switching behavior relates to price changes of the bundle purchased. This figure shows the distribution of the difference between the price for the bundle purchased and the price the consumer would have paid if they had bought the same bundle at the other platform. On the left is the distribution for consumers that never switched away from the first platform they chose and on the right is the same distribution for consumers that chose to switch at some point. This provides motivating evidence that switching is rational: even if the consumer has a subscription to a service and incurs a cost to switch, if prices are more attractive at the competitor, they are more likely to switch. These differences in prices across retailers are an important source of variation identifying the model in the next section.

[6] No grocery delivery company shared more than 13% percent of another company's customers (2019): https://secondmeasure.com/wp-content/uploads/2019/08/GroceryDelivery-chart3_v2.png

Table I. *Demand Identification: Data Switching Patterns*

	s' = *no subscription*	s' = *Big Tech*	s' = *Grocer Partner*
s = *no subscription*			
Fraction of Purchases	99.83%	0.16%	0.01%
s = *Big Tech*			
Fraction of Purchases	0.21%	99.61%	0.18%
s = *Grocer Partner*			
Fraction of Purchases	0.29%	0.34%	99.37%

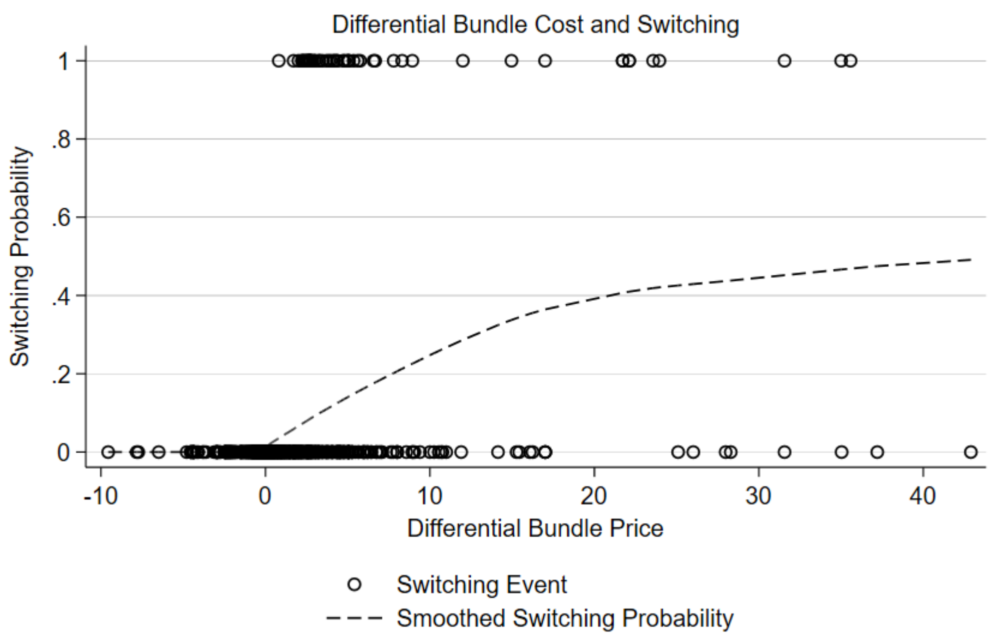
Table II. *Average Number of Days Since First Purchase*

	To *Big Tech*	To *Grocer Partner*	To no Subscription
Switch from *Big Tech*	-	428 days	304 days
Switch from *Grocer Partner*	285 days	-	82 days
Obs 2,411			

Note: Statistics based on platform user purchases in 2015-2017 across online and offline channels. s is the consumer's subscription status inferred from past purchases and s' is the subscription choice inferred from the current purchase choice.

Identification of the demand model also relies on variation in choices made by consumers across demographic groups and geographic characteristics. Table IV shows how the characteristics of users of each delivery service compares to the average panelist. Table V shows distances traveled by households when brick-and-mortar retailers are chosen and how the cost of the bundle of products bought compares across retail channels. As previously mentioned, there are important differences in the delivery logistics used by each service 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 (IV) shows how the demographic characteristics of customers differ across the two services. As *Grocer Partner* relies on the pre-existing retailing alternatives in an area, is more 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 (IV). Conversely, by having a centralized distribution system, *Big Tech* serves a continuous radius centered in the downtown area of the cities it operates in: as shown in figure (VI). This is more likely to include lower income neighborhoods, even if not purposefully. This is reflected on the characteristics of users: *Big Tech* has a larger share of users who are in the lowest income group ($< 45K$) than the *Grocer Partner*, as shown in table IV.

Figure I. *Price Variation and Switching*



Note: Each observation is a price difference of the combined products purchased compared to the other platform when the consumer has the opportunity to switch to purchase the same bundle. The smoothed predicted probability is predicts whether the consumer switched platforms, given the price difference of the bundle purchased.

Finally, identification of switching costs in the demand model make use of price variation in bundles purchased. Figure (I shows how prices paid by consumers for the bundle of products purchased related to switching behavior. I compute the difference between prices paid and prices at the alternative platform for consumers that have access to both choices. The figure maps price differentials against an indicator of switching associated with the individual and a smoothed outcome measure of the switching probability. Individuals that have purchased bundles with higher differential prices are more likely to eventually switch between platforms. This is preliminary evidence that switching is at least partially driven by prices and, therefore, rational. However, high price differences still predict a switching probability below 50%, indicating that small price differences are not enough to induce switching. These two fact combined indicate that price comparisons for the bundle chosen are a source of switching identification and that, at the same time, consumers may incur additional costs of switching not captured by bundle price differences. These additional costs may be sunk payments due to subscription sign-up fees or other costs perceived by consumers, such as the cost of time spend comparing prices between platforms. I do not distinguish between such types of sunk costs in the demand model. Instead, I infer the combined sunk costs that rationalize switching behavior in the data in order to reproduce demand dynamics under the assumption of that the price scheme is unchanged.

III. EVIDENCE OF ENTRY TIMING AS A STRATEGIC DECISION

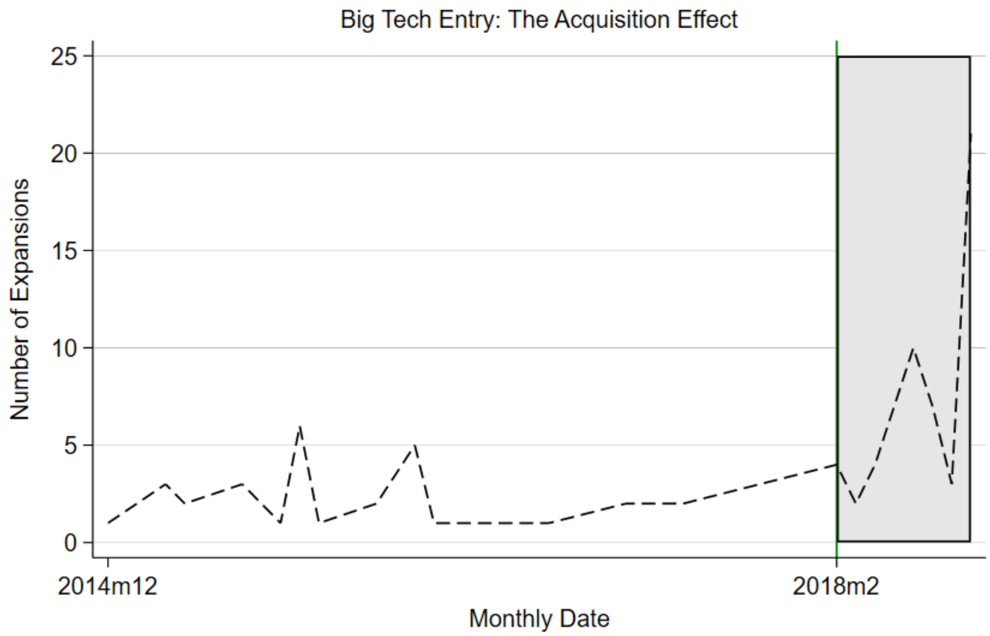
In this section, I describe how entry and coverage patterns differ between the two firms and provide suggestive evidence of how they interact strategically. Figure (IV) shows the roll-out of grocery delivery services across the US.

As previously mentioned, the two platforms competing in the game presented in section (IV) have very distinct cost structures. This is relevant to understand how they make use of different strategies impacting their speed of entry. *Big Tech* makes use of fulfillment centers dedicated to same-day grocery delivery. Before this platform is launched in a new location, it builds a new fulfillment center and traces a continuous delivery radius around it. *Grocer Partner* makes use of pre-existing stores belonging to retail partners. Figures (V) and (VI) show how this impacts their geographic footprint. Whereas the former has a continuous coverage, the latter has often pockets of covered zip codes geographically close. These business model differences are relevant to understand the entry strategies each firm can make use of and their costs. *Big Tech*'s model is expected to lead to high entry costs and distribution costs that decrease significantly with population density. Conversely, *Grocer Partner*'s implies low entry costs, as no infrastructure needs to be built to operate. This also means that the speed with which each firm can make entry decisions is likely to be different. For example, if *Grocer Partner* believes *Big Tech* is likely to enter a certain market soon, it is more likely to enter early as a response if its entry cost is low. The evidence presented next is compatible with these features of the firms' costs.

The motivating evidence of the two platforms' strategic interaction uses the timing of the event in which *Big Tech* acquired a grocery chain. Around the time of the announcement, there is a spike in the number of *Grocer Partner*'s entry decisions across new markets, as shown in figure (II). Table (VI) measures the effect using a Poisson regression. Because this firm's business model relies on making use of pre-existing stores, its entry cost should be low. Consequently, it reacts to the rival's announcement immediately with entry across new markets where, with the acquisition, *Big Tech* is expected to enter sooner. Effectively, *Big Tech* only starts making use of the newly acquired store as delivery hubs six months after the acquisition. Figure (III) shows the faster rate of entry once the firm has its entry cost reduced by the acquisition.

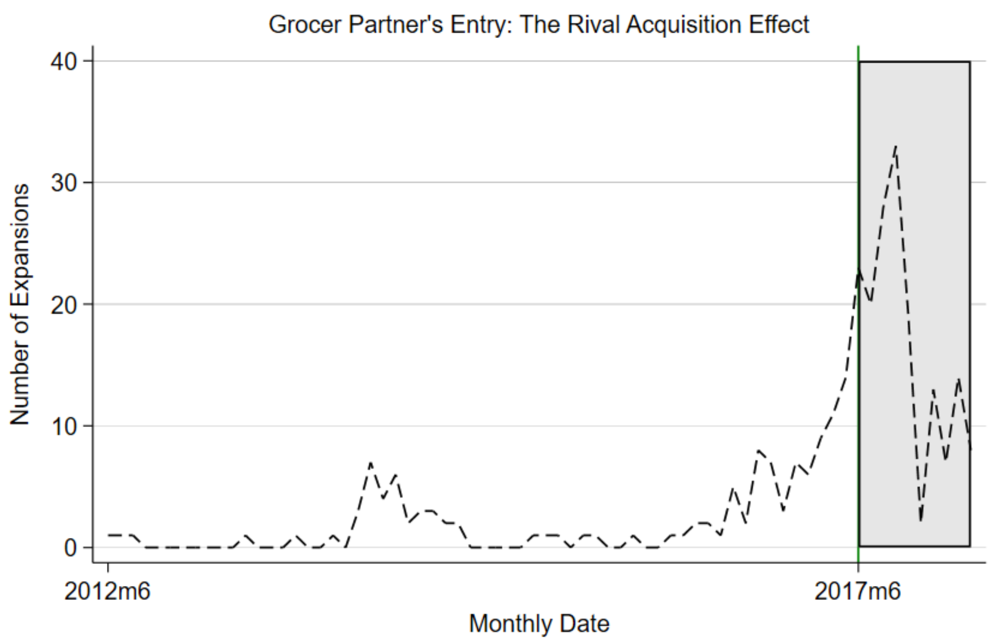
This is the key motivating evidence for the first merger counterfactual conducted using the duopoly game. It shows that the timing of the firms' entry decisions and, in particular, their strategic interaction in this dimension can be quantitatively important. Combined with the motivating evidence of lock-in, this justifies the choice of a model where forming a base of subscribers is a driving force of entry timing and where the consequences of a merger can be evaluated in terms of strategic entry timing. Moreover, in the model I allow for entry costs to vary over time and estimate the rate of change to capture how firms' technology may be evolving over time.

Figure II. *Acquisition Lowers Big Tech Entry Costs: Faster Entry*



Note: Each observation is the sum of entry decision announcements made by Big Tech in a month. Announcements are collected on the firm's social media pages and press releases. The increase in entry decisions in 2018 corresponds to the time when Big Tech starts using the acquired stores as delivery hubs.

Figure III. *The "Big Tech Effect": Rival Reaction to Acquisition Announcement*



Note: Each observation is the sum of entry decision announcements made by Grocer Partner in a month. Announcements are collected on the firm's social media pages. The spike in entry decisions in 2017 corresponds to the time when Big Tech publicly announces the acquisition of Grocer Partner's largest grocery chain partner.

III. Demand Model

Many grocery delivery services require a subscription membership payed monthly or yearly to use the service. This is the case of *Big Tech*'s grocery delivery service where consumers need a membership to a set of benefits and this membership includes grocery delivery at no additional cost. *Grocer Partner* offers a yearly subscription membership that costs approximately $\$150$ and includes unlimited delivery at no additional cost. Since consumers' subscription status are not directly observed, I infer it through purchases. Consumers in the data don't switch back and forth between the two services and multi-homing (using more than one platform simultaneously) is also does not happen. Consequently, I only consider the three mutually exclusive alternatives of consumer status: $s \in \{$*No Subscription (0), Big Tech (B), Grocer Partner (G)*$\}$. This variable is an indicator of whether the consumer has purchased from either firm in the past.

The demand model reflects the different aspects of consumer choice observed in the data. As an observation is a purchase decision for a panelist, there isn't a fixed period between choices. For this reason, I assume consumers receive utility shocks associated with products they might want to buy in continuous time. A purchase decision then occurs as a result. Conditional on a purchase being observed in the data, I model the consumer's utility over the observed and unobserved aspects of the decision: subscription, retailer and bundle of products chosen. I then use a revealed preference approach to identify the relevant sets of parameters.

I. Consumer Problem

For each consumer i, consider a dynamic single-agent decision problem in which time is continuous and an arrival process governs when decision opportunities indexed by $t = 1, 2, ...$ are made. At any time, the state for i is the subscription status inherited from the last decision period $s \in \{0, B, G\}$. When a decision opportunity arrives, the consumer chooses to update the subscription s', conditional on the current state s and a random utility component (ϵ). The individual also makes shopping decisions conditional on the updated subscription s' and ϵ. Shopping decisions are bundle ($b \in \mathcal{B}$) and retailer ($j \in J_{s'}$) choices with indirect utility:

$$U_{s'}(\epsilon) = \max_{\{b \in \mathcal{B}\}, \{j \in J_{s'}\}} u_{bj} \tag{1}$$

The indirect utility is in the spirit of (Katz 2007). There is a structural random utility component which is bundle, consumer and time-specific: ϵ. To not burden the notation, I omit all individual and time subscripts and discuss below which components are observed at the individual and time levels. The utility of purchasing a bundle of products b at retailer j is:

$$u_{bj} = V_b + (-1 + \alpha Y)P_{bj} + X_j(\beta_0 + Z\beta_1) + T_j(\gamma + \eta) + \epsilon_b \tag{2}$$

P_{bj} is the expenditure required to buy b at j which is specific to purchase t and the price paid by the individual is observed. This includes any promotions i may have received to buy the bundle, which are observed in the data. The baseline price elasticity is normalized to be -1 which means that the remaining parameters are expressed in dollar terms. Additionally, the elasticity is allowed to differ according to the individual's income Y and the parameter α.

Z_1 are demographic variables which affect i's preferences for retailer characteristics (X_j) which are subsumed by a fixed-effect for each retailer. This fixed-effect provides an estimate for any differences in quality not captured by other observables[7]. The retailer fixed-effect controls are then used to address the price endogeneity issue associated with quality and evaluate how retailer preferences vary across demographic groups. T_j is the distance between i and retailer j's closest store, if j is a brick-and-mortar retailer. The utility of the bundle has one constant and one random component. V_b is the mean utility associated with the bundle of goods purchased. ϵ_b is the random utility component associated b observed by the consumer when making the purchase (in t) but, unknown to the researcher. Consequently, this error is a high-dimensional object defined over all possible products the consumer can buy $b \in \mathcal{B}$ in a decision period. Finally, η is a constant component of i's in travel cost also unobserved by the researcher and approached econometrically as random coefficient, as done in (Katz 2007).

[7]This is a control for what would be the unobserved quality of the product ξ_j in a typical discrete choice setting.

A1: *Unobserved preferences for bundles and retailers are separable.*

A1 is assumed in specification (2). This is same assumption imposed in (Katz 2007) in order to perform the revealed preference approach to identify the parameters in (2). This means that retailer quality does not depend on the bundle purchased and can, therefore, be measured as a retailer fixed-effect. Even though retailer quality doesn't vary with b, prices vary across retailers, bundles and periods. If consumers have some information about prices before making decisions, this rationalizes the fact that consumers don't always buy the same things and from the same retailers. Firstly, this means that the cheapest retailer for a particular bundle isn't the same across periods. Secondly, after considering both prices and other dimensions of retailer quality that are invariant across bundles, the optimal retailer choice can vary across periods.

The problem solved by consumer during a decision period is then:

$$V(s, \epsilon) = \max_{s' \in S} \{u_{s'}(\epsilon) - C(s, s') + \beta E[V(s', \epsilon')|s']\} \tag{3}$$

Where $C(s, s')$ is a cost function which depends on the state and the subscription choice. The discount factor β combines the expected length of the random interval between the current trip and the next decision and the consumer's is the discount factor in continuous time. The expectation is taken over future bundle shocks and number of future trips.

The cost of subscription changes is assumed to be:

$$C(s, s') = \begin{cases} c_{BG}, & if \quad s = B \quad and \quad s' = G \\ c_{GB}, & if \quad s = G \quad and \quad s' = B \\ c_{0B}, & if \quad s = 0 \quad and \quad s' = B \\ c_{0G}, & if \quad s = 0 \quad and \quad s' = G \\ 0, & otherwise \end{cases} \tag{4}$$

Costs of subscribing to each service is a sunk cost $c_{ss'}$ which depends on which subscription $s \in$

$\{0, B, G\}$ the individual held at the time of the service change to s'. Moreover, the cost of termination - choosing absence of subscription ($s' = 0$) - is always assumed to be zero for the identification reasons discussed in the next section.

II. DEMAND IDENTIFICATION: REVEALED PREFERENCE

I first discuss the identification of utility parameters θ. I show there is a set of revealed preference relations that generate moments for these parameters which are identical to a setting such as (Katz 2007)'s. I then derive the set of moments which are used to estimate continuation values and subscription costs.

ii.1 Identification of Utility Parameters

Suppose a consumer receives a decision shock in period t, they choose (b, j) to solve equation (1). If the separability assumption **A1** holds true, we can compare the utility value associated with each alternative retailer $k \neq j$ such that $k, j \in J_{s'}$ holding the subscription and bundle chosen fixed. By holding the bundle fixed, the difference in utility across retailers is independent of the bundle chosen, reducing the set of parameters to be estimated. Moreover, by holding the subscription fixed, costs associated with maintaining or switching between subscriptions are differenced out along with continuation values. To see this, let b denote the bundle bought at retailer j and $\tilde{b}$ denote the optimal bundle the consumer would have bought at an alternative store k.

Let I be the individual's information set when making such decision. Suppose the state is s optimally makes a subscription decision s'. The revealed preference relation between the individual's choice and their utility when the optimal bundle $\tilde{b}$ associated with the alternative retailer choice k is:

$$E[u_{bj} - c_{ss'} + \beta EV(s', \epsilon')|I] \quad \geq \quad E[u_{\tilde{b}k} - c_{ss'} + \beta EV(s', \epsilon')|I], \quad \forall k \in J_{s'} \tag{5}$$

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:

$$E[u_{\tilde{b}j} - c_{ss'} + \beta EV(s', \epsilon')|I] \quad \geq \quad E[u_{bk} - c_{ss'} + \beta EV(s', \epsilon')|I], \quad \forall k \in J_{s'} \tag{6}$$

By transitivity, joining the last two inequalities yields:

$$E[u_{bj} - c_{ss'} + \beta EV(s', \epsilon')|I] \quad \geq \quad E[u_{bk} - c_{ss'} + \beta EV(s', \epsilon')|I], \quad \forall k \in J_{s'} \tag{7}$$

Note that both sides of this inequality have identical terms with the exception of u_{bj} and u_{bk}. Consequently, it simplifies to:

$$E[u_{jb}|I] \geq E[u_{k\tilde{b}}|I] \quad ie, \quad E[\Delta u_{bjk}|I] \geq 0 \tag{8}$$

This last inequality is the key implication of consumer behavior used for estimation. It implies that, for any purchase (b, j), we can hold the bundle b and the subscription s' fixed and compare the utility of this observed choice with the utility of the alternative choice (b, k) as long as k is also a retailer available in $J_{s'}$. Re-arranging this result and using the specification from equation (1) we get:

$$E[\Delta u_{b,jk}|I] = E[(-1 + \alpha Y)\Delta P_{bjk} + \Delta X_{jk}(\beta_0 + Z_1\beta_1) + \Delta T_{jk}(\gamma_0 + \eta)|I] \geq 0 \tag{9}$$

Note that, not only are subscription costs and continuation values differenced out but, so are both terms associated with the bundle utility: V_b, the mean bundle utility and ϵ_b, the unobserved bundle shock. As as result, we have a set of inequalities that depends only on retailer choice utility parameters.

The measured moments that are used to estimate the vector of parameters θ of the utility are:

$$\Delta\tilde{u}_{b,jk}(s;\theta) = (-1 + \alpha Y)\Delta\tilde{P}_{bjk} + \Delta\tilde{X}_{jk}(\beta_0 + \tilde{Z}_1\beta_1) + \Delta\tilde{T}_{jk}(\gamma_0 + \eta) \geq 0 \tag{10}$$

ϵ would be a *structural error* according to (Pakes et al. 2015)'s classification of types of error that can arise in this setting (labeled ν_2 in their setting). Ignoring this type of error can cause important bias.

Differencing this out implies that these moments are valid regardless of the characteristics of this random variable which avoids problems with making additional specification assumptions. The term η is source of unobserved heterogeneity known to the consumer that can also be a source of bias if ignored. This term is addressed with a normalization with respect to the traveled distance for the trip (when it's offline). Details of this normalization can be found in (Katz 2007). Another type of error that can arise in this setting is *measurement error* (ν_1 in (Pakes et al. 2015)). This includes expectational errors and other examples discussed next.

Measurement errors enter naturally in the model. This is the case for the expectational error that would arise if the incorrect bundle is used to measure equation (10). If the consumer based their purchase decision on bundle b' instead of b, an error of this sort would correspond to the difference between the expenditure for these two bundles: $\nu_1 = \Delta P_{bjk} - E[\Delta P_{b'jk}|I]$. It should then be the case that $E[\nu_1|I] = 0$ and, consequently,

$$E[\Delta\tilde{u}_{bjk}|W] = E[\Delta u_{bjk}|W] = E[\Delta u_{b'jk}|I] + E[\nu_1|I] = E[\Delta u_{b'jk}|I] \geq 0 \tag{11}$$

Where $\tilde{u}_{bjk}$ is the difference in utility measured and W are the instruments used for the consumer's information set[8]. Further details on this type of expectational error can be found in (Katz 2007).

Since current prices are observed in the data, the inequality (9) is measured directly from the data for a set of alternative retailers k that are good comparisons to choice j. 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 UPCs in the bundle 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 2015-2017 period. For each trip, alternative retailers will be the two closest retailers and the two retailers with most similar cost, resulting in a total of 4 inequalities per observation.

Although these moments recover θ without dealing with the computation of future values, they cannot

[8] See (Hansen and Singleton 1982) for details on the instrumentation in rational expectation models using sample counterparts to the population orthogonality conditions.

be used to estimate fixed and sunk costs as those parameters are differenced out in relation (9). For this reason, I discuss next how I use a second set of revealed preference relations to estimate these costs.

ii.2 Identification of Subscription Costs

Define the choice specific value function, conditional on s':

$$V(s, s'\epsilon) = u_{s'}(\epsilon) - c_{ss'} + \beta E[V(s', \epsilon')|s'] \tag{12}$$

By optimality, if the consumer chooses s' conditionally on state s:

$$E[V(s, s', \epsilon)|I] \geq E[V(s, \tilde{s}, \epsilon)|I], \quad \forall \quad \tilde{s} \in S \tag{13}$$

Joining the last two inequalities yields:

$$\begin{aligned} E[u_{s'}(\epsilon) - c_{ss'} + \beta E[V(s', \epsilon')|s'] \quad |I] \quad &\geq \quad E[u_{\tilde{s}'}(\epsilon) - c_{s\tilde{s}} + \beta E[V(\tilde{s}, \epsilon')|\tilde{s}] \quad |I] \\ &\Leftrightarrow \\ E[\Delta u_{b,jk} - c_{ss'} + c_{s\tilde{s}} + \beta(E[V(s', \epsilon')|s'] - E[V(\tilde{s}, \epsilon')|\tilde{s}] \quad |I]) \quad &\geq \quad 0, \quad \forall k \in J_{\tilde{s}} \end{aligned} \tag{14}$$

Under the standard assumption that the random utility component is $i.i.d$ over time, we get:

$$E\Delta V_{s'\tilde{s}'} = \Delta E V_{s'\tilde{s}'} \equiv E[V(s', \epsilon')] - E[V(\tilde{s}', \epsilon')] \tag{15}$$

The inequality (14) should then hold conditionally on the bundle and retailer (j) chosen by i, similarly to (9). It then yields:

$$E[\Delta u_{b,jk} - c_{ss'} + c_{s\tilde{s}} + \beta E\Delta V_{s'\tilde{s}}|I] \quad \geq \quad 0, \quad \forall k \in J_{\tilde{s}} \tag{16}$$

Using (10), the inequality above is measured as:

$$
\begin{aligned}
(-1+\alpha Y)\Delta\tilde{P}_{bjk} + \Delta\tilde{X}_{jk}(\beta_0 + \tilde{Z}_1\beta_1) + \Delta\tilde{T}_{jk}(\gamma_0 + \tilde{Z}_2\gamma_1 + \eta) & \\
-F_{s'} - c_{ss'} + F_{\tilde{s}'} + c_{s\tilde{s}'} + \beta E\Delta\tilde{V}_{s'\tilde{s}'} \quad \geq \quad 0, \quad \forall k \in J_{\tilde{s}'} & \qquad (17)
\end{aligned}
$$

In order to compute this second set of moments for a candidate $\{\hat{\theta}, \hat{F}, \hat{f}, \hat{c}\}$, we need to compute the term $E\Delta\tilde{V}_{s'\tilde{s}'}$. So, I use of optimality conditions to impose bounds on these value differences. The estimation proceeds in two steps. I first estimate the utility parameters (θ) using solely the first set of moments, following (Pakes et al. 2015) and (Katz 2007). Secondly, I use these estimated parameters and rationality constraints to compute the differences in continuation value across alternatives[9]. The second set of moments is then evaluated to estimate switching costs. Section (i) presents demand estimation results.

IV. Entry Model

In the data, I observe both firms' entry decisions at the time they announce the service is launching in a new location. The time between decisions are then not fixed (e.g. annual or quarterly) and decisions are observed in continuous time. Moreover, features of both firms' distribution costs and revenues suggest that markets are independent. Indeed, *Big Tech*'s operation of same-day grocery delivery is done through a separate online platform created for this purpose. The fulfillment centers used for this service are also separate from its other online retail operations. Each market gets a dedicated hub built exclusively for this type of delivery. This makes sense given that grocery and fast delivery require products to be shipped locally, unlike other product categories. For *Grocer Partner*, deliveries are fulfilled from local partner stores. Even though the platform partners with chains that have national presence, the decision of which stores are used has only local implications and restrictions. These features motivate the choice of the model that follows.

[9] Details in appendix.

I. ENTRY GAME SETUP

Two firms $i \in \{B, G\}$ make strategic entry decisions within each independent market $m \in \{1, 2, ..., M\}$. Time is continuous and two independent Poisson processes with parameter $\lambda_i, \quad i \in \{B, G\}$ govern decision opportunities for each firm in a market. When facing an entry opportunity, the firm observes an exogenous state $B_i \in \{0, 1\}^M$ which indicates in which market the firm can choose to make an entry decision. The firm also observes the distribution of subscribers in the market which indicates whether their rival is present and how many customers have already been locked-in: N_m.

For each move arrival in m, the *Big Tech* firm (B) can choose to enter ($j = 1$) if it wasn't already serving m and makes no further choices otherwise. Ie, the firm chooses $j \in \{0, 1\}$ if $N_{Bm} = 0$. Given a chance to move, the *Grocer Partner* (G) firm can choose to enter ($j = 1$) if it wasn't already serving the market ($N_{Gm} = 0$) and expand coverage ($j = 2$) if it already had market presence ($N_{Gm} > 0$). Neither firm can exit markets served. The stock of subscribers N_{im} in each market determines the firms' flow revenues:

$$R_i(N_m) = \bar{r}_i N_{im}, \quad i = B, G \tag{18}$$

Where $\bar{r}_i$ is i's average revenue per customer, including subscription fees and consumers' purchase expenditures. When B enters market m, it needs to build a fulfillment center (FC). The size of the FC can differ across markets and is a measure of the firm's scale in each location: F_{Bm}. Operating a larger FC can imply larger fixed costs and the firm's flow profit parameter β_{B1} captures this effect. Firm G needs partnerships in each market in order to operate and expand. This firm's number of partners in each market increases over time along with its coverage (figure VII). The number of partners F_{Gm} can affect the firm's fixed and variable cost of delivery through parameters β_{G1} and β_{G2}. Finally, the market's population density affects each firm's variable costs through β_{B2} and β_{G3}.

Firm B's flow profits in market m are then:

$$\pi_{Bm} = \mathbf{1}_{z_{Bm}=1}[\bar{r}_B N_{Bm} + \beta_{B0} + \beta_{B1} F_{Bm} + \beta_{B2} d_m + \beta_{B3} h] \tag{19}$$

Firm G's flow profits in market m are:

$$\pi_{Gm} = \mathbf{1}_{z_{Gm}>0}[(\bar{r}_G - \beta_{G2} F_{Gm}) N_{Gm} + \beta_{G0} + \beta_{G1} F_{Gm} + \beta_{G3} d_m + \beta_{G4} h] \tag{20}$$

Where h is an unobserved market state. Each firm also pays a sunk costs to enter which are allowed to vary over time to capture firms' ability to expand at lower costs after entering many markets and to rationalize the increase in the frequency of entry for both firms observed in the data. Choice-specific sunk payoffs for B are then:

$$\psi_B = \begin{cases} \kappa_{B0} + \kappa_{B1} h + \kappa_{B2} t & if \quad j = 1 \quad \& \quad N_{Bm} = 0, \\ 0 & otherwise \end{cases}$$

Firm G also pays an expansion cost which can differ from the entry cost. Entry costs for this firm are then:

$$\psi_G = \begin{cases} \kappa_{G0} + \kappa_{G1} h + \kappa_{G2} t & if \quad j = 1 \quad \& \quad N_{Gm} = 0, \\ \eta_{G0} + \eta_{G1} h + \eta_{G2} t & if \quad j = 1 \quad \& \quad N_{Gm} > 0, \\ 0 & otherwise \end{cases}$$

II. Law of Motion of Subscribers

The inequalities from the demand model imply subscription decisions for each consumer given a bundle choice. Evaluating these decisions for each of the three possible service availability cases (B alone, G alone and both B and G in the market) for a sample of consumers generates frequencies of subscription choices, conditional on each state. These frequencies are estimates for transition probabilities that represent the law of motion of subscribers in a market for each service availability case. Let m be a market where consumers have characteristics X_m. The transition matrix $M(X_m)$ describes the aggregate transition across subscription states of consumers in m. N_m describes distribution of subscribers in m across $\{0, B, G\}$.

$$\dot{N}_m \quad = \quad M(X_m)N_m \tag{21}$$

The transition will depend on which services are available in m. Therefore, we can define the following cases:

$$M(X_m) = \begin{cases} M_B(X_m), & if \quad z_{Gm} = 0 \\ M_G(X_m), & if \quad z_{Bm} = 0 \\ M_{BG}(X_m), & if \quad z_{im} > 0, \forall i \\ I_3, & otherwise \end{cases}$$

Where z_{im}, $i = \{B, G\}$ is an indicator equal to 1 if firm i's service is available in m.

N_{im} for each firm is independent of characteristics of any other market. Firm costs in each market are independent of distribution centers and retail partners in other locations. Indeed, in each metro area, *Big Tech* builds a dedicated distribution center specialized in this same-day delivery operation. And, *Grocer Partner* relies on stores close to the consumers being served. Moreover, availability of both services is determined by the consumer's zip code and is highly correlated with the distance to the local FC (for B) and closest partner stores (for G). Consequently, assuming that markets are separable and firm entry decisions are made at the market level is appropriate. This implies that the exogenous state determining constraining in which market the firm can make an entry decision, given an opportunity to move, can be expressed at the market level: B_{im}.

Following the value function formulation in (Arcidiacono et al. 2016), each firm's problem for a specific market is expressed as:

$$V_{ik} = \frac{\pi_{ik} + \lambda_{-i} \sum_{j\in\{0,1\}} q_{-i}\sigma_{-ijk} V_{i,\ell(-i,j,k)} + \lambda_i q_i E\{V_{i,\ell(i,j,k)} + \psi_{ijk} + \epsilon_{ijk}\}}{\rho + +q_{-i}\lambda_{-i}\sigma_{-ijk} + q_i\lambda_i} \tag{22}$$

Where q_i is the probability that $B_{im} = 1$.

Section (V-ii) presents the estimation steps and profit estimation results.

V. RESULTS

I. DEMAND ESTIMATION RESULTS AND SUBSTITUTION PATTERNS

The estimates for the revealed preference model are presented in tables (VII) to (X). The first table shows the results for the parameters where I interact each firm fixed-effect with household characteristics. All parameter estimates are in dollars per shopping trip and, the estimates of the interactions between demographic variables and each firm's fixed-effect can be directly interpreted as differences in consumer surplus after normalizing by the cost elasticity for that group[10].

The parameter results show the different channels through which consumers benefit form these online retail alternatives. An important dimension for benefits generated for consumers is the distance to offline alternatives and variety of offline alternatives in the consumer's vicinity. 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 *Big Tech* and *Grocer Partner* less valuable by $\$0.36$ and $\$0.44$, respectively. Between 1 and 5 miles the effect for *Big Tech*'s service is much smaller (a negative effect of $\$0.04$) and, the effect for *Grocer Partner*'s service is positive: an additional retailer between 1 and 5 miles increases the value of

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

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 closely to a zip code the more partnerships *Grocer Partner* will offer and the more value this service will generate to consumers.

In order to disentangle the effect from *Grocer Partner*'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 column (2) I add the number of partners offered by *Grocer Partner* 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 *Big Tech* and *Grocer Partner*'s 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 *Grocer Partner*'s 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. Zip codes with an average income of up to $45K$ that are served by *Grocer Partner* 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 *Grocer Partner* 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 *Grocer Partner* 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 *Grocer Partner* 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 *Grocer Partner*'s service and $\$0.49$ to the value to of *Big Tech*, 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.

Other demographic characteristics that matter for welfare are age and gender (table (VII)). 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 *Big Tech* and up to $\$0.79$ for *Grocer Partner* per shopping trip.

I conduct a counterfactual to measure how responsive consumers are to a change in the value of each subscription. The goal is to measure how much, in the presence of subscription lock-in, firms can raise prices in the long run. I compute these subscription elasticicities for each service in two scenarios: when the consumer can choose to switch to the competitor and when there is no competition. Table XI shows the counterfactual results for a change in the subscription value of $-\$20$ that simulates an increase in the subscription fee by the same amount or an equivalent change in prices goods sold through each platform. I find that consumers have a similar response to such a change in the value of the *Big Tech* subscription compared to *Grocer Partner* in the case where both alternatives are available. In this case, 50% of subscribers would switch from *Big Tech* to *Grocer Partner* if *Big Tech* had a price increase of this magnitude. 46% would switch from *Grocer Partner* to *Big Tech* if *Grocer Partner* were the firm increasing prices. In the absence of the rival, switching patterns are very similar for *Grocer Partner* but quite different for *Big Tech*. When the rival is not available to the consumer, only 36% of subscribers would switch away from *Big Tech*'s service whereas 45% would switch away from *Grocer Partner*. This shows that the latter is a much closer substitute to other available alternatives such as brick-and-mortar grocers. This makes sense, given that this firm offers delivery from stores that are located close to the consumer. An implication of these results is that, having another platform competing with *Big Tech* is important for keeping prices low in the long run.

II. Estimation of Profit Parameters and Results

The estimation takes place in two steps. First, I estimate reduced-form entry hazards for each firm using a logit with parameters varying by firm:

$$\tilde{\sigma}_{ij}(k, z, \alpha) = \frac{exp(\phi_j(k, z, \alpha))}{\sum_{j' \in \mathcal{A}_{ik}} exp(\phi'(k, z, \alpha))} \tag{23}$$

Where $\phi(k, z, \alpha)$ is a linear function of state variables and z the market's unobserved state. The specification estimated is:

$$\phi^i(k,z,\alpha) = \alpha_1^i + \alpha_2^i * pop_m + \alpha_3^i * pop_m^2 + \alpha_4^i * income_m + \alpha_5^i * t + \alpha_6^i * F_{Gm} + \alpha_7^i * N_{-im}$$

Let $h(\alpha) = (\lambda_B \sigma_B(k,z,\alpha), \lambda_G \sigma_G(k,z,\alpha)))$ be the choice hazards. In a second step, the profit structural parameters (θ) are estimated. The value function is expressed as a function of the structural parameters and the first-stage hazards $h(\hat{\alpha})$. The hazards are used to solve for the value function using *Proposition 4* in (Arcidiacono et al. 2016) and generate structural hazards $\Lambda(\theta, \hat{h})$. The second-step pseudo-likelihood then uses the structural hazards to estimate $\hat{\theta}$ using Maximum Likelihood.

Tables (XIII) and (XIV) show the estimates for the firms' profit parameters. The first important difference between firms is captured by entry costs. Entry cost at time 0 for *Big Tech* is approximately the equivalent to 1 year of the average market's variable profits. The entry cost at time 0 for *Grocer Partner* is only 8% of the average market's yearly variable profits for this firm. This explains why *Grocer Partner* enters faster across markets and its pattern of entering markets by steps with progressive expansions across pockets of zip codes. Another key difference in cost structures captured by model parameters is in scale economies and the importance of population density to lower unit distribution costs. Whereas *Big Tech* has large fixed costs which increase with the size of its distribution center in a particular market, *Grocer Partner* does not. Fixed costs for the latter are estimated using the number of partnerships by market, which estimates show have more important effect on revenues than costs. On the other hand, *Big Tech*'s distribution costs fall with population density at a much faster pace than *Grocer Partner*'s. This is consistent with the fact that *Big Tech* basically stopped expanding across new markets using same-day grocery fulfillment centers after entering the largest (and densest) markets in the U.S and after acquiring stores that could be used as distribution hubs instead. Figure (VIII) shows the growth in population coverage of the two firms and *Big Tech*'s shift towards expansion with stores after the acquisition. Conversely, *Grocer Partner* continues to expand across smaller and sparser markets. Figure (IX) shows the decrease in average market size (population) covered by *Grocer Partner*.

VI. Counterfactuals

The first counterfactual exercise measures the importance of early entry to firms' entry decisions. I use an approach similar to Schmidt-Dengler (2006)'s to measure preemption. I compute a Nash Equilibrium where firms pre-commit to their entry times and removing the incentive to for early entry[11]. Each firm then chooses entry strategies consistent with the belief that their rival commits to the pre-commitment equilibrium. Table (XV) shows the average time in years since the beginning of the game (June 2012) it takes each firm to enter the markets in sample. Entry decisions generated by the model with early entry incentives are such that *Big Tech* enters markets on average after 3.55 years and *Grocer Partner* after 3.97, considering expansion decisions. In the counterfactual with commitment, it takes *Big Tech* on average 4.68 years to enter a market and 5.20 years for *Grocer Partner*. Entering earlier means higher entry costs but potentially higher variable flow profits due to subscriber accumulation and rival deterrence. I compute payoffs for each firm in each equilibrium across markets to measure producer surplus losses due to early entry. Losses for *Grocer Partner* are the highest, amounting to 31.34% of its average payoff. As shown in table 4, this firm's entry cost decrease over time at a much faster rate than *Big Tech*'s. This effect is identified by the increasing rate with which the firms enter markets over time. And it drives high relative losses of early entry for this firm. Early entry also implies important losses for *Big Tech*. On average, this firm gives up 10.84% of its payoff in each market due to early entry - table (XVI).

The second exercise measures the effects of a merger between *Big Tech* and a grocery chain. The acquisition allows the firm to enter markets faster because the stores bought can be immediately used in the grocery delivery operation. This allows the firm to forgo during the period following the acquisition (2018-2019) the entry cost that exists in the model. The entry timing for the post-merger period is observed in the data for two years. I compare these observed decisions with the timing predicted by the estimated pre-acquisition model for those markets (out of sample). In the model, the firm pays a high entry cost (table 4) to enter these new markets. In particular, for *Big Tech*, entry costs are as high as one year of variable profits. With the acquisition, the firm can enter markets faster by not paying these costs by market, explaining the faster rate with which it expands during the period following the merger. Comparing the

[11] This approach yields very similar results to one where switching costs are removed and consumers' transition (and revenues) is as table (XII) on the right.

model with the data, I find that the firm gains on average 2.51 years of in speed of entry across new markets. The result is similar for the competitor, who enters 2.41 years faster as a result. The rationale for the faster entry of *Grocer Partner* in the data compared to the model is that the merger raised the stakes on entry for this firm as well. The firm responds to the rival's faster entry potential due to the acquisition by accelerating its own entry decisions and take advantage of consumer lock-in.

The third exercise analyses the consequences of a merger between *Big Tech* and *Grocer Partner*. The merged firm is a monopolist whose base of subscribers ($\tilde{N}_M$) is the sum of subscribers to both services: $\tilde{N}_M = N_B + N_G$. Due to the absence of competition, choice hazards do not include the other firm's N. In each market, the monopolist's cost is the minimum between making use of the FC network or the set of partners. In other words, the monopolist chooses the business model in each market that yields the highest payoff. In a more sophisticated setup, the monopolist's business model could be hybrid and the firm would be able to choose what version of the service to offer to different zip codes. This is probably relevant for consumer welfare if the value of each service differs across locations in the same market. I focus for now on the entry timing effect which shouldn't be affected by the possibility of a hybrid business model. Results for this counterfactual are presented in table (XIX). The results show that, in the absence of the threat from a competitor to generate a barrier to future entry through lock-in, the firm does not have an incentive to enter markets earlier. This shows the role of competition in promoting entry of new products across markets. Indeed, I find that consumers would lose $ 2.04 Billion in welfare across the geographical markets that eventually were served exclusively due to delayed entry by the monopolist. That does not include the effects of possible future price increases by the monopolist. Indeed, as shown in table (XI), the *Big Tech* service at least is not a close substitute to existing alternatives. Consequently, in the markets where the monopolist chooses this cost structure there would be an incentive to increase prices in the future as consumers as less likely to unsubscribe as a response to a price increase. Finally, table (XIX) also shows the proportion of markets where the monopolist would choose each business model. *Big Tech* makes use of large fixed costs and has also larger economies of density, as its distribution cost is more strongly reduced with population density. In only approximately 20% of markets served this would be the most efficient cost structure. In the other 80%, *Grocer Partner*'s model of decentralized distribution is the most profitable choice.

VII. Conclusion

This paper provides an empirical framework to study the relationship between strategic entry timing and consumer welfare in a setting where consumer lock-in is a driving force of entry. I study the entry timing decisions of two firms with distinct business models. Differences between business models allow me to distinguish entry incentives driven by cost structure from consumer lock-in. I do so by using data on two platforms offering grocery delivery in a variety of U.S. markets. The model is a useful setup for both demand a supply-related questions relevant for current antitrust policy discussions around digital platforms. First, I measure the importance of consumer lock-in due to switching costs associated with subscriptions, a pricing strategy widely used in e-commerce and other platform-enabled markets. Second, I model the relationship between demand dynamics and supply timing decisions in an empirically tractable way. Then, by relating these two sides, I measure the importance of the demand mechanism to firms' entry strategies.

Results show that sunk costs associated with subscriptions generate significant inertia in platform choice. In absence of switching costs, consumers would switch ten times more often across services. This inertia in customer base makes firms' decision to enter markets time-sensitive, as entering late comes with the cost of having to breach the barrier of consumer lock-in created by the rival. On the other hand, entering early implies higher entry costs and the efficiency loss associated with this incentive is, on average, 10% of producer surplus for the firm with high fixed costs and 30% of producer surplus for the firm with high variable costs.

I use the model to evaluate the impact of two types of mergers for consumer welfare and efficiency. Each merger has very different implications for each of these outcomes, showing that timing of entry is an important dimension to be considered in merger and welfare analysis in markets where a new product being gradually introduced through geographic entry. The first is the acquisition of a grocery chain by *Big Tech*. This merger reduced the entry cost of a firm for which this was the main entry barrier. This allowed the firm to enter markets much quicker following the acquisition. In contrast, the firm's rival with low entry costs responded to the acquisition by increasing the pace of its own entry decisions immediately after the acquisition announcement by *Big tech*. In the model, this is captured by the rival's expectation that *Big Tech* will establish consumer lock-in by accumulating subscribers in new markets faster than before.

This then increases the payoff of early entry for *Grocer Partner*. As a consequence, many markets that would only receive one or both services over 8 years after the first platform is created get them more than 2 years earlier. Even though this merger may have other consequences that are important for competition and consumer welfare which are not within the scope of this paper, it fostered consumer welfare through strategic entry timing.

Conversely, a merger that establishes a monopoly in the delivery market has the opposite effect. If *Big Tech* decides to buy off *Grocer Partner*, the consequence predicted is a significant slow down in entry speed. In particular, if this merger had occurred at the beginning of the entry game, consumers would have gained access to these technologies at least 6 years later, on average. Again, this is without considering any dimension for which market structure would also be relevant for, including the incentive to create these services in the first place. Finally, this framework can be used to analyze many other markets that blend digital technology and offline cost structures that are under the antitrust scrutiny today. Indeed, timing of access to particular geographical markets is a crucial factor to a firm's decision to buy another business. And, more importantly, the way competitors' are expected to react, given features of demand, is an important factor to consider when analyzing whether the acquisition is harmful to consumers of not.

A. Figures and Tables

Figure IV. *National Roll-out of Grocery Delivery Services (2014-2017)*

(a) *2014*

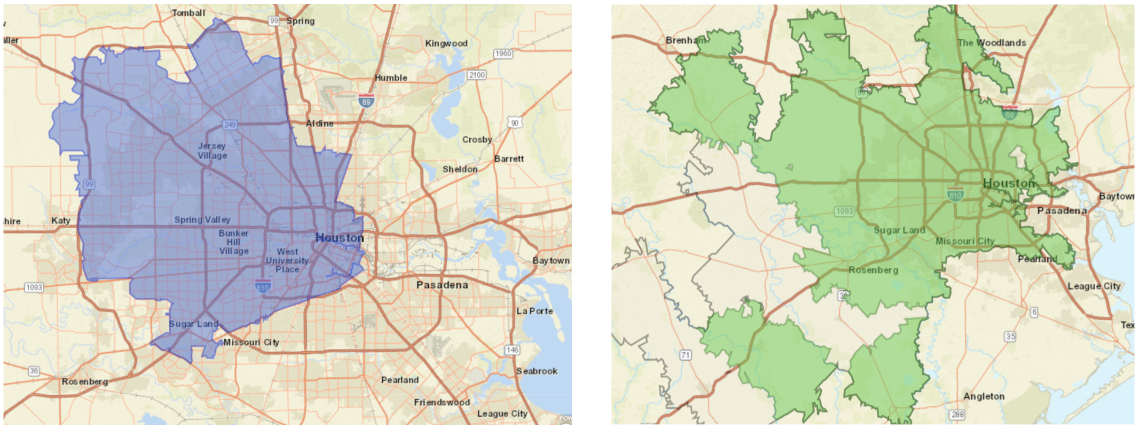
(b) *2015*

(c) *2016*

(d) *2017*

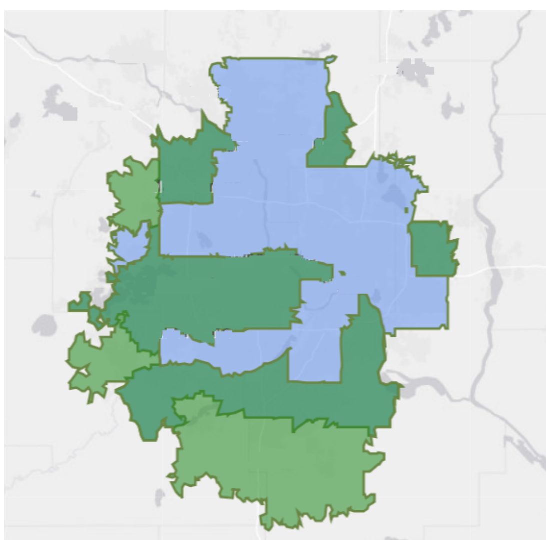
Note: Each colored pin represents a different grocery delivery service. Big Tech is represented by blue squares and Grocer Partner by green pins. Yellow and red pins represent two other grocery delivery services with regional coverage for scale, showing how Big Tech and Grocer Partner's coverage compare.

Figure V. *Zip Codes Served by Big Tech and Grocer Partner*



Note: Example of delivery radius for a metro area in the sample. Zip codes are used to match households' location and service availability. Zip codes in blue are served by Big Tech and, zip codes in green are served by Grocer Partner by the end of the sample period.

Figure VI. *Local Geographical Market Coverage: Big Tech and Grocer Partner*



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 Big Tech, zip codes in light green are uniquely served by Grocer Partner and the dark green area corresponds to zip codes served by both firms.

Table III. *Urban Areas and Player Moves (2012-2017) in Supply Estimation*

Area Name	Pop (million)	Density (thousand)	Entry - B	Entry/Expansion - G
Atlanta	7.45	6.63	1	6
Baltimore	2.25	24.90	1	4
Boston	3.24	40.00	1	5
Charlotte	0.98	6.20	1	3
Chicago	8.76	30.24	1	8
Cincinnati	2.39	10.61	1	2
Columbus	2.31	2.72	1	3
Dallas	4.78	3.51	1	7
Denver	0.40	15.48	1	2
Detroit	3.80	6.96	0	2
Houston	4.13	19.01	1	4
Indianapolis	4.46	4.84	1	2
Jacksonville	1.91	9.24	0	2
Los Angeles	6.64	22.98	1	12
Memphis	0.87	4.49	0	1
Miami	5.02	10.05	1	6
Milwaukee	3.54	13.69	1	1
Minneapolis	4.01	12.88	1	4
Nashville	2.53	2.73	1	3
New York	7.02	78.52	1	11
Omaha	1.52	7.05	0	1
Orlando	3.15	5.23	1	4
Philadelphia	3.45	31.94	0	9
Phoenix	2.10	4.52	1	3
Raleigh-Durham	0.20	4.36	1	2
Richmond	2.67	7.10	1	2
San Antonio	1.26	7.32	1	5
San Diego	2.38	13.17	1	5
San Francisco	3.99	58.81	1	9
St. Louis	2.73	5.02	0	2
Tampa	4.46	7.87	1	5
Washington DC	5.29	32.20	1	8

Note: Population of area is calculated by adding the population of all zip codes within a 30 miles radius around the local Big Tech fulfillment center or the city town hall zip when there is no FC. Population density is the population-weighted density by distance from city hall (miles) in 2010 Census.

Table IV. *Demographic Characteristics of Panelists*

	Sample	*Big Tech* Customers	*Grocer Partner* Customers
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 binary. 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 V. *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

Note: Each observation is a purchase associated with the relevant channels in the data during 2015-2016. Table (Va) presents the mean dollar value of the bundles purchased in trips associated with each channel. Table (Vb) presents the mean distance between panelists and the closest store of each channel.

Table VI. *The "Big Tech Acquisition" Effect*

	(1)
VARIABLES	Number of Grocer Partner Entry Decisions
Time (Monthly Date)	0.0270***
	(0.00529)
Post-Acquisition Announcement	0.708***
	(0.202)
Constant	-17.19***
	(3.525)
Observations	76

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

Note: Each observation is a month with the the number of new entry announcements (coinciding with the launch date in that market) made by Grocer Partner. The post-announcement period is of 6 months following the day Big Tech publicly announces the acquisition of a grocery chain.

Table VII. *Revealed Preference Estimates (in $): Demographics*

	(1)	(2)
Big Tech * Under 30	2.39	3.09
	[2.36, 2.44]	[3.04, 3.14]
Big Tech * Income [45K - 70K)	7.36	10.85
	[7.24, 7.47]	[10.65, 10.98]
Big Tech * Income > 70K	10.51	7.84
	[10.34, 10.68]	[7.64, 7.94]
Big Tech * Single Female	0.228	0.543
	[0.225, 0.232]	[0.532, 0.551]
Grocer Partner * Under 30	2.15	1.66
	[2.12, 2.19]	[1.62 1.69]
Grocer Partner * Income [45K - 70K)	0.00132	0.00081
	[0.00130,0.00134]	[0.00079, 0.00082]
Grocer Partner * Income > 70K	9.10	13.25
	[8.96, 9.25]	[12.97, 13.40]
Grocer Partner * Single Female	0.79	0.36
	[0.78, 0.80]	[0.35, 0.36]
Retailer Fixed-effects	YES	YES
η	NO	YES

Table VIII. *Revealed Preference Estimates (in $): Consumer's Geographic Characteristics*

	(1)	(2)
Big tech * Retailers < 1 mile	-0.181	
	[-0.185, -0.179]	
Big Tech * Retailers < 5 miles	-0.041	
	[-0.040, -0.041]	
Big Tech * Closest Store (miles)		0.461
		[0.452, 0.467]
Grocer Partner * Retailers < 1 mile	-0.979	
	[-0.995, -0.963]	
Grocer Partner * Retailers < 5 miles	0.335	
	[0.329, 0.340]	
Grocer Partner * Nb G Partners		1.428
		[1.400, 1.444]
Grocer Partner * Closest Store (miles)		0.342
		[0.335, 0.346]
Retailer Fixed-effects	YES	YES
η	NO	YES

Table IX. *Revealed Preference Estimates (in \$): Travel Cost and Income-Price Elasticity*

	(1)	(2)	(3)	(4)
Income * Price (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]
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
η	NO	YES	NO	YES

Table X. *Switching Cost Estimates (\$)*

	s' = *Big Tech*	s' = *Grocer Partner*
s = *no subscription*	\$ 4.50	\$ 13.87
	[4.13, 5.12]	[12.89, 14.92]
s = *Big Tech*	-	\$ 11.05
		[8.13, 11.93]
s = *Grocer Partner*	\$ 6.74	-
	[6.24, 7.54]	
Subscription Fixed Cost	0.9	0.99
	[0.76, 0.91]	[0.97, 1.26]

Note: Costs of switching across states. Costs include all fees in a per-purchase base as well as any other type of switching costs implicit in consumers' decisions. Confidence intervals are computed using the confidence intervals on utility coefficients. For each bound on first set of parameters, I solve for the second set of moments to get bounds on switching costs.

Table XI. *Subscription Value Reduction and Subscriber Substitution*

	With Rival	Without Rival
% Δ in *Big Tech* market share when $\Delta V_B = -\$20$	-51%	-36%
% Δ in *Grocer Partner* market share when $\Delta V_G = -\$20$	-46%	-45%

Table XII. *Model Predicted Transitions: With (left) and Without Switching Costs (right)*

	$s' = 0$	$s' = B$	$s' = G$
$s = 0$	0.9804	0.0134	0.0062
$s = B$	0.0074	0.9883	0.0042
$s = G$	0.0114	0.0048	0.9838

	$s' = 0$	$s' = B$	$s' = G$
$s = 0$	0.6015	0.1082	0.2902
$s = B$	0.0227	0.6304	0.3469
$s = G$	0.2124	0.3142	0.4733

Figure VII. *Grocer Partner's Store Partnership Growth*

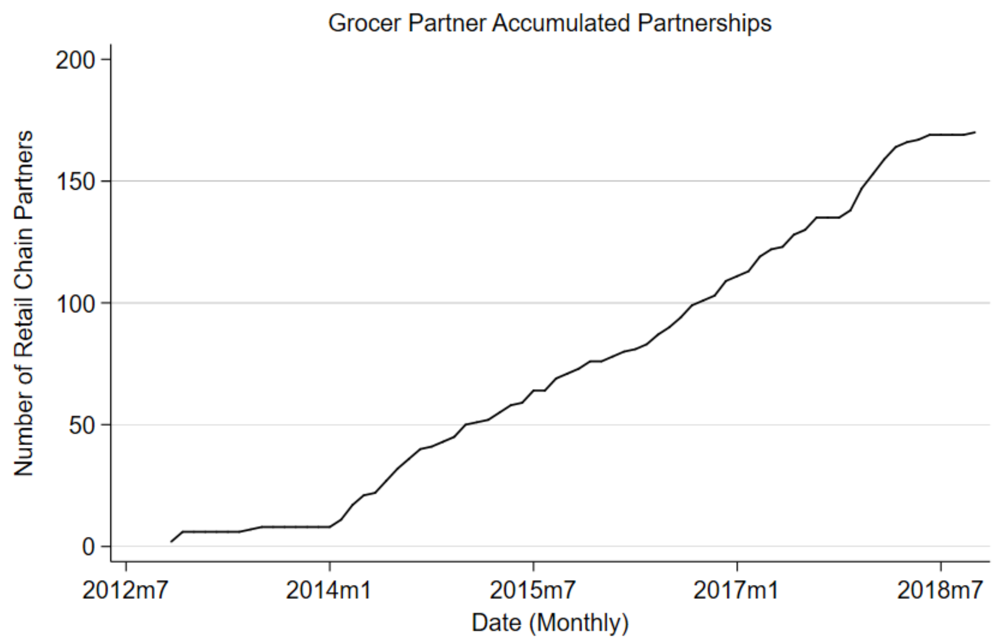


Table XIII. *Flow Profit Parameters*

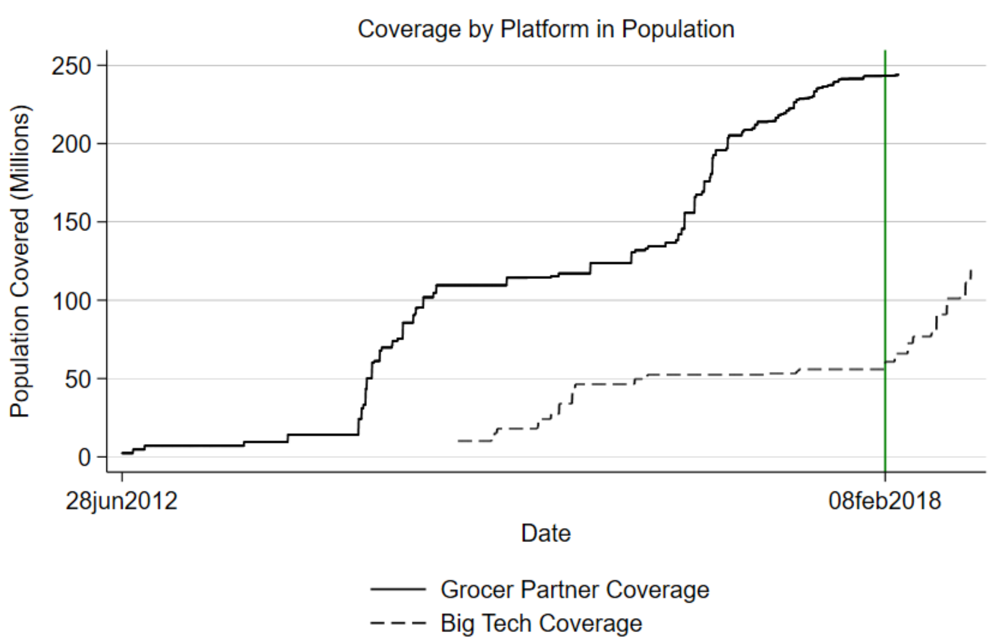
	Big Tech (1)
Constant	-0.356
	(0.189)
FC Size (sq-ft)	-19.298
	(1.116)
Market Pop Density	71.118
	(8.615)

	Grocer Partner (1)
Constant	26.958
	(1.034)
Partners (Fixed Cost)	-0.068
	(0.005)
Market Pop Density	1.278
	(0.505)
Partners (Revenue)	18.748
	(8.514)

Table XIV. *Entry Costs*

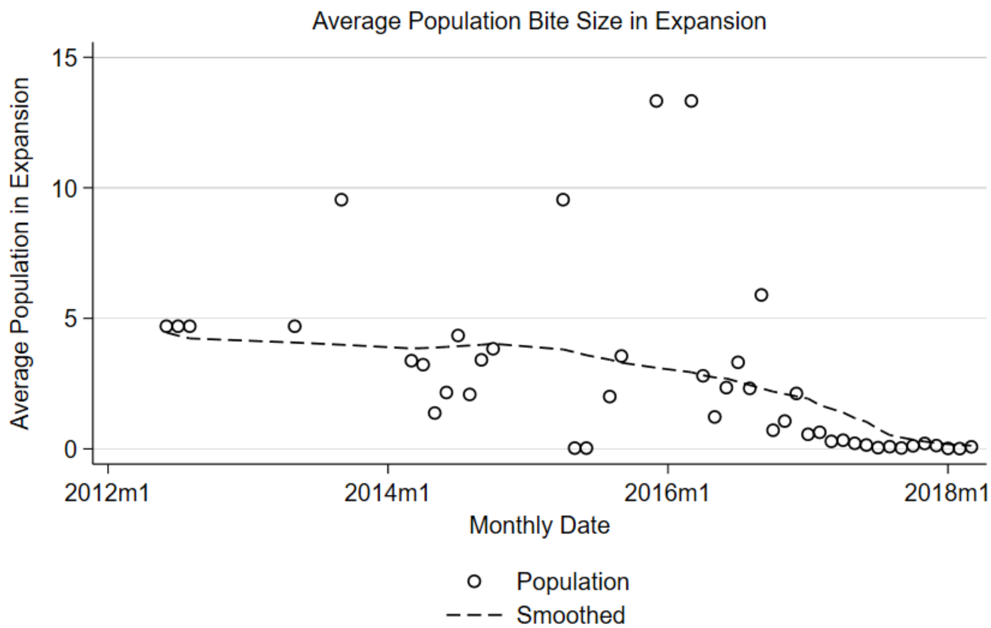
	(1)
Big Tech	-72.746
	(12.455)
Big Tech * Time	9.822
	(1.469)
Grocer Partner - First Entry	-5.244
	(0.821)
Grocer Partner * Time	35.239
	(3.924)
Grocer Partner - Expansion	-5.548
	(2.487)

Figure VIII. *Total Population Served by Firm*



Note: Accumulated population served by firm over time. Population is calculated by summing over confirmed served zip codes in each market after entry is announced. The vertical line represents the date when Big Tech announces the first entry using the acquired stores.

Figure IX. *Markets Entered by Grocer Partner: Population*



Note: This graph shows the average size in population in Grocer Partner's expansions averaged over each month. At the end of the period observed, markets are as small as 300 thousand people.

Table XV. *Measuring Early Entry*

	Lock-in and Competition	Pre-Commitment Equilibrium
Average Time to Entry *Big Tech*	3.55	4.68
Average Time to Entry *Grocer Partner*	3.97	5.20
Total Number of Obs	169	169

Note: Average time in years until entry decision across markets, conditional on there being entry for the firm until December 2017. Time is counted since first entry occurrence in June 2012. For Grocer Partner, all entry decisions in market are considered.

Table XVI. *Early versus Late Entry Payoffs*

%Δ Average Payoff *Big Tech*	10.84 %
%Δ Average Payoff *Grocer Partner*	31.34%
Number of Delayed Entries *Big Tech*	79
Number of Delayed Entries *Grocer Partner*	66
Total Efficiency loss	20.17%
Total Number of Obs	169

Table XVII. *Big Tech Merger with Brick-and-Mortar: Entry Timing*

	Post-Merger (2018-2019)	No Merger
Average Time to Entry *Big Tech*	6.18	8.69
Average Time to Entry *Grocer Partner*	4.73	6.87
Total Number of Obs	30	30

Note: Average time in years until entry decision across markets where neither firm had yet entered until June 2017. Time is counted since first entry decision by either player (June 2012).

Table XVIII. *Merger: Welfare Gains and Losses*

%Δ Average Payoff *Big Tech*	10.05 %
%Δ Average Payoff *Grocer Partner*	6.41 %
Number of Anticipated Entries *Big Tech*	28
Number of Anticipated Entries *Grocer Partner*	27
Total Efficiency loss	624 ($ M)
Total Consumer Welfare Gain	846 ($ M)
Total Number of Obs	30

Table XIX. *Monopoly Counterfatcual - Big Tech Merges with Grocer Partner*

Monopolist's Average Time to Entry	10.10
Share of Markets with *Big Tech* Business model	20.64%
Efficiency Gain	1.66 ($ B)
Welfare Loss	2.04 ($ B)
Total Number of Obs	169

Note: Average time in years until entry decision across markets where neither firm had yet entered until June 2017. Time is counted since first entry decision by either player (June 2012). Monopolist chooses most profitable business model by market. Gain from monopoly accounts for cost savings from lack of early entry and efficiency gains due to scale economies.

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