Where to Next? Mobile Broadband and Business Dynamics

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Abstract

I study the impact of mobile broadband access and smartphone adoption (together, "smartphone access") on business dynamics. Using point-of-interest data in conjunction with estimated 3G access, I find that smartphone access favors establishments and firms that were already prominent prior to this technology becoming available. Rollout decreased establishment churn and increased the proliferation of large regional and national firms. Regarding location decisions, I find no evidence to support a change in new entrants' distance to incumbent establishments, likely due to the size of relocation costs.

JEL Codes: L11, R12, R3

Keywords: 3G, smartphones, competition, Google Maps

1 Introduction

Search is critical to firms; if consumers cannot find a firm, then that firm will sell no products and earn no profits. This simple fact helps explain why firms pay higher rents for high-traffic or high-visibility locations and invest heavily in advertising as they compete for consumer attention. But consumer-facing industries have undergone significant changes in recent decades. Large firms in the service sector have increasingly standardized their processes and operate locations in more markets (Hsieh and Rossi-Hansberg, 2023), leading many firms to become less geographically concentrated. On the other hand, the advent of smartphones has dramatically changed consumers' search process. Going beyond the yellow pages of the past, modern "virtual directories" like Google Maps help consumers find businesses, guide consumers to their destinations, and serve as hubs for reviews. This gives prospective customers easier access to information than ever before, but to what effect?

In this paper, I examine how a change to consumer information—specifically, establishment information becoming accessible by smartphone—changed the results of interfirm competition. To accomplish this, I leverage a rich data set containing detailed information on firm industry and location across time, combined with estimated historical 3G access across the continental United States. My treatment, "smartphone access," is based on 3G coverage after smartphones began gaining traction. I follow previous literature and

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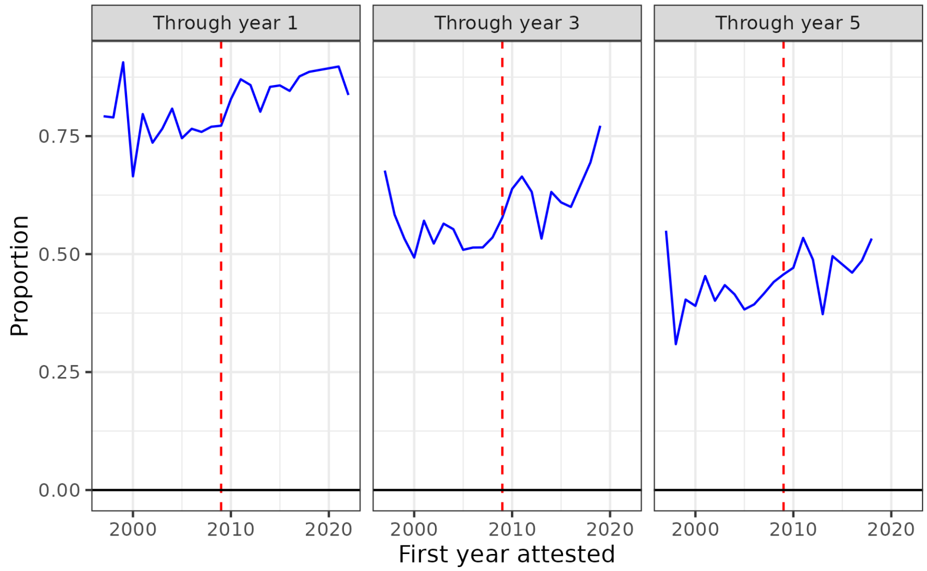
Figure 1: Changes in establishment survival rates across time



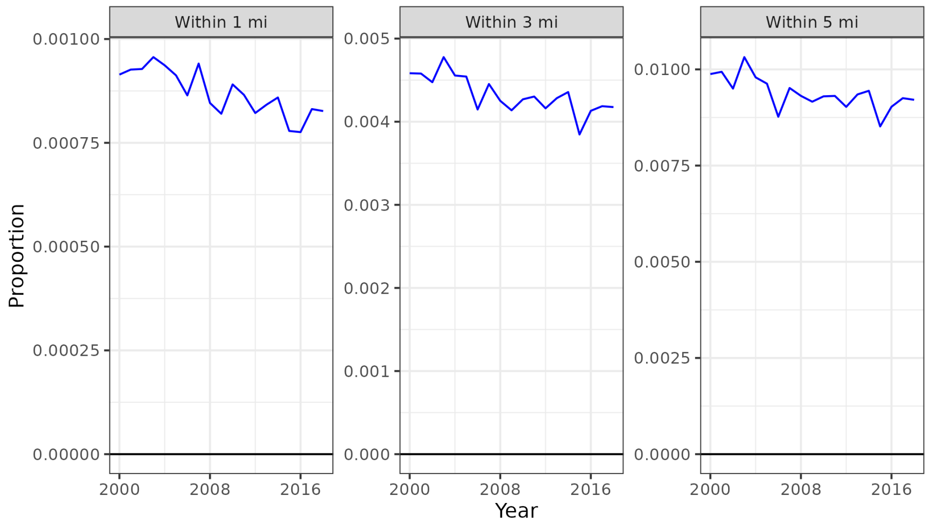
Notes: Calculations derived from Data Axle Historical Business Data (HBD), 1997-2019. This figure depicts the overall survival rate across consumer-facing industries, based on the year of first observation in the data set. Said industries consist of NAICS codes beginning with 44-45, 52, 53, 71, and 72. Year of first observation may not be the same as the year of first opening, especially for 1997. Survival rates are calculated by taking the count of establishments who opened in year t, and seeing what proportion of those are open in years $t+1$, $t+3$, and $t+5$. The red line indicates the year 2009.

the importance of the iPhone 3G (released in Q3 2008) in using 2009 as the point at which smartphones were sufficiently widely adopted to matter.

To preview my results, I find that areas with greater smartphone access after 2009 see counts of new and closing establishments decrease across all industries, with new entry decreasing by around 10% of the mean. The decline in closures is concentrated in consumer-facing industries, with an estimated effect that is 22% of the mean. I also identify small positive effects on the likelihood that consumer-facing establishments remain open in the short term (1-5 years after entry), though these results should be taken more as suggestive evidence. Among new entrants in consumer-facing industries, a significantly higher proportion are part of large regional/national firms (0.5 percentage points, 17% of the mean). Taken together, these results indicate that the effect of consumer smartphone access favors incumbents and large firms. While location choice is a common way that firms pay for prominence, I find only very small changes in establishment location decisions; I reject any changes in the distance from new entrants to their nearest competitor greater than a couple hundred feet, to no practical effect.

First, consider what we may expect to happen as consumers gain access to virtual directories on their smartphones. I construct a theoretical model in Section 3 to explore the effects of better information in more detail. Intuitively, however, consumers often change their behavior when exposed to more information about firms they may patronize (Luca, 2016, Jin and Leslie, 2003), especially as that information relates to firm quality. If higher-quality firms are more likely to survive into future periods, incumbent establishments have a higher expected quality—though consumer review data may allow new entrants to distinguish themselves by providing a more accurate signal of quality to consumers. Shocks to information provision could contribute to the changes in firm survival rates shown in Figure 1, based on when a firm was first observed. Prior to 2009, the rate at which consumer-facing firms survive for one, three, or five years remains relatively consistent, but survival rates all *increase* in 2009. There is some indication of these rates trending upwards in subsequent

Figure 2: Changes in establishment co-location across time



Notes: Calculations derived from Data Axle Historical Business Data (HBD), 2000-2018. Using a random subsample of firms in all industries across the United States, this figure outlines the proportion of bilateral distances *between* firms that are below certain thresholds. Data is recorded annually.

years, but this initial spike did not persist.

Because Internet use makes it easier for prospective consumers to find a business to patronize, reducing the search costs and frictions that encourage co-location in the first place (Nilsson and Smirnov, 2016, Vitali, 2022), we may expect smartphones to allow firms to locate further from their competitors. Knowing a firm's quality may induce some to travel further to patronize that firm as well. Figure 2 illustrates the proportion of bilateral distances—the distance between two establishments chosen at random—that fall below one, three, or five miles. And indeed, since 2000, there has been a slow decline in the proportion of businesses clustering near their peers, and an increase in the proportion that are geographically "isolated" from other firms in a given industry.

This project contributes to several strands of existing literature. I primarily build on the body of work exploring the effects of Internet access on firm outcomes, largely centered on productivity. Extensive research finds that fixed-connection Internet (via ethernet, or home Wi-Fi) increases firm productivity (Cardona, Kretschmer, and Strobel, 2013; Barrero, Bloom, and S. J. Davis, 2021; Jiang, 2023) and entrepreneurship (Conroy and Low, 2022; Biedny, Whitacre, and Van Leuven, 2024[1]). The literature dealing with specifically *mobile* broadband is more limited; while Bertschek and Niebel (2016) finds a positive effect on productivity in Germany, few other studies exist.

Recent research goes beyond productivity, though cell phones are more often used as *indicators*, not determinants, of consumer behavior (for examples, see Glaeser, Kim, and Luca, 2018; D. R. Davis et al., 2019; and Miyauchi, Nakajima, and Redding, 2021). In this paper, I follow the approach in Hersh, B. J. Lang, and M. Lang (2022), an exception to this trend, studying how 3G rollout in California resulted in increased car accidents. The authors use a random forest to predict historical 3G coverage where it is not available, and also focus specifically on the adoption of smartphones from 2009 onward as their source of treatment.

I also contribute to the literature on consumer search and information. Empirical research has consistently

[1]For a review on rural broadband, see Mack et al., 2024.

shown that consumers respond to new, especially negative, information. Poor online reviews are predictive of business closures (Kong et al., 2017; Tao and L. Zhou, 2020; Purba, Pasha, et al., 2024) and reduced restaurant revenue (Luca, 2016). When restaurant health grades are required to be displayed on the outside of a business, negative reports lead to declines in consumer demand (Jin and Leslie, 2003). Market frictions can also shape firm behavior, including location decisions. Firms cluster more when consumer information is costlier to acquire (Dudey, 1990; Murry and Y. Zhou, 2020; Moraga-González, Sándor, and Wildenbeest, 2023), in part because clusters become focal points for consumers to travel to. On the consumer side, theoretical work by Albrecht, H. Lang, and Vroman (2002) and Kennes and Schiff (2008) suggest that better-informed consumers avoid low-quality firms, which survive by selling to the uninformed. By reducing search costs and increasing consumer knowledge, smartphones and mobile broadband could reduce firm clustering and make low-quality businesses less viable.

Such shifts tie my work to the wider literature on firm location choice, such as research examining industry-level agglomeration (Ellison and Glaeser, 1997; Duranton and Overman, 2005; Bartelme and Ziv, 2023; Bartelme and Ziv, 2024). An important distinction is that the majority of this research focuses on broad, regional agglomerations and metropolitan specialization. The goal of papers like Ellison and Glaeser (1997) and Duranton and Overman (2005) is to understand how specialization occurs at a very broad level, such as the level of the United Kingdom in Duranton and Overman (2005). This paper is more concerned with the local than the regional, as is Leonardi and Moretti (2023), which examines restaurant location dynamics after a policy change in Milan. That paper's results come as descriptive graphs or maps, rather than attempting to use measures of firm location as a specific outcome, which I do.

The rest of the paper is organized as follows: Section 2 provides more background for the adoption of smartphones and 3G broadband. Section 3 outlines the potential costs and benefits to consumers and firms. Section 4 provides more information on the data I use, and Section 5 outlines the methods I employ. Section 6 presents my findings, and Section 7 discusses them.

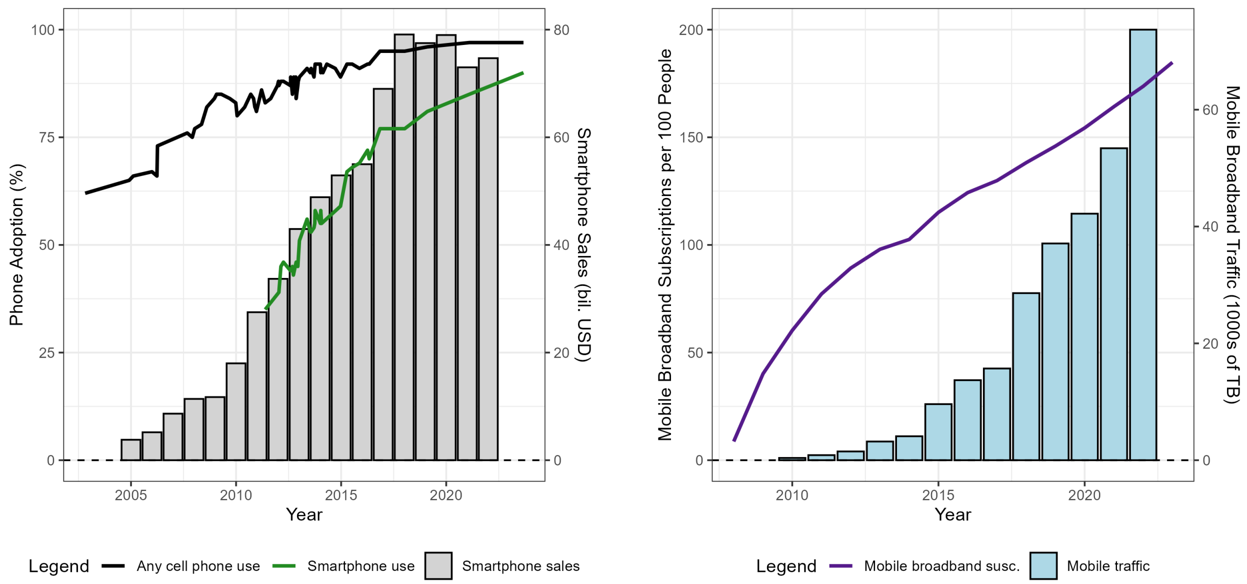
2 Background

In 2000, the majority of U.S. cell service consisted of 2G, which is sufficient for encrypted voice and text communication; the basic form of 2G has a maximum speed of 50 Kilobits per second (Kbps).[2] This speed is too slow for consumers to comfortably go online, as a page of Google results[3] is about 250kb, requiring approximately five seconds to load at top speed. 3G, a standard finalized in 1998 but not implemented in the United States until the early to mid 2000s, was significantly faster, with a maximum speed of 2 Megabits per second (Mbps), forty times faster than the previous standard.[4]

Prior to the rollout of 3G, consumers were effectively unable to access the Internet via their mobile devices, as even the fastest connection speeds were simply too slow for a usable browsing experience. While still slower than a contemporaneous wired connection, 3G was substantially faster than previous mobile standards. As it became more common, manufacturers began to release devices capable of taking advantage of 3G's faster speeds, though these devices' interfaces did not keep up. 3G-capable phones were generally traditional "dumb phones" despite their upgraded connection capabilities. While devices like BlackBerries had the capacity to go online and send emails, these were *not* the typical 3G-capable devices—and in fact, the

[2]Source: `https://www.lifewire.com/1g-vs-2g-vs-2-5g-vs-3g-vs-4g-578681`
[3]Examined in 2025.
[4]ibid.

Figure 3: Smartphone and mobile broadband adoption



(a) Smartphone adoption

(b) Mobile broadband adoption

Notes: Panel (a) uses data on cell phone use from Pew Research (2024), and data on smartphone sales from Statista and the Consumer Technology Association. Panel (b) uses data on mobile broadband from the FCC (accessed via ITU) and mobile traffic from the CTIA. All data accessed in March 2025.

company's 2009 Curve 8900 model was only 2G-compatible![5] The first modern, touchscreen smartphone[6]—the Apple iPhone—debuted in 2007, with the 2008 release of the iPhone 3G bringing the first 3G-compatible phone with an interface truly suitable for mobile Internet use to market.

By 2008, many American consumers already had some kind of cell phone, and smartphone adoption was rapid—by 2013, a majority of American adults reported having a smartphone,[7] just six years after the invention of the category. Figure 3 depicts this near-exponential increase in smartphone adoption and mobile broadband use across time. Panel (a) shows how sales and adoption closely followed each other, with the industry already worth $18 billion by 2010, and well over $25 billion the following year. Not only were consumers buying these devices, they were using them while on the go. Panel (b) demonstrates the rapid increase in both sales and utilization of mobile broadband subscriptions, with subscription rates exceeding 100 per 100 people by 2014.[8] The amount of mobile data used increased exponentially over the same period.

While consumers could and did make use of a variety of websites and mobile applications ("apps") on their smartphones, the most relevant application in this context is Google Maps. "Maps" is a computer and mobile interface for getting directions and exploring points of interest, and was launched on the web in February 2005. Later that same year, it launched for mobile phones as well.[9] Maps allows users to "find

[5]Source: `https://www.slashgear.com/1092246/the-most-iconic-blackberry-phones-of-all-time/`

[6]While devices such as those produced by BlackBerry predated the iPhone, and for market purposes, are often considered early smartphones. This is why Figure 3 has positive sales for the smartphone industry in 2005. As such devices do not fit the modern conception of a smartphone, and would be cumbersome to browse the Internet with, I do not consider them true "smartphones."

[7]Source: `https://www.pewresearch.org/Internet/fact-sheet/mobile/`

[8]This reflects business subscriptions, as consumers are unlikely to need more than one mobile broadband connection per device.

[9]Source: `https://web.archive.org/web/20160406123606/http://www.google.co.uk/about/company/history/#2005`

local businesses, get point-to-point driving directions, and view live traffic updates,"[10] though the early mobile implementation was unavailable to most consumers. Predating the rise of the modern smartphone by around two years, Maps could instead be used on Blackberries, Windows Mobile devices, and Palm products. By 2007, it was updated to include user reviews, about three years after Yelp was first released.[11] On smartphones, adoption of Maps was all but automatic from the release of the first iPhone until 2012, when Apple launched its own competing software.[12] Before then, all iOS and Android devices came preinstalled with Maps. Despite now having some competition, Maps has continued to dominate in review quantity, hosting an estimated 73% of all business reviews in 2022.[13]

I now turn to a suggestive overview of how the use of Maps or a similar virtual directory may change the search process for consumers and the discovery process for firms.

3 Conceptual framework

Consider a Hotelling-type market in which residents are distributed according to a piecewise function, such that there is a denser "downtown" at $x \leq \gamma$ and and sparser "suburban" area for all $x > \gamma$.[14] Define the mass of consumers as H for $x \leq \gamma$ and L otherwise, such that there is a unit mass of consumers: $\gamma H + (1-\gamma)L = 1$. For a visual example of the market, refer to Figure 4.

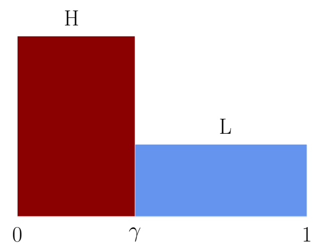


Figure 4: Distribution of consumers

Two firms a and b decide where to locate, $x_a,\ x_b$ s.t. $x_a < x_b$, to attract consumers and earn a profit. I assume the market is fully covered, such that all consumers have incentive to travel to and purchase from one of the firms. Consumers do not gain the same utility from consuming at firm a and firm b; rather, $\rho \in [0,\ 1]$ proportion of consumers prefer firm a, and $1-\rho$ prefer firm b. Consumers do not know which type they are, but do know ρ and the payoffs for a good and bad match, $(u_g,\ u_w),\ u_g \geq u_w$, such that they can use an expected payoff to determine where they choose to go.

Consumers' travel cost from point x to x_i, $i \in \{a, b\}$ is given by $|x - x_i|$. Given x_a and x_b, the consumer at s is indifferent between x_a and x_b at

[10] Source: https://googlepress.blogspot.com/2007/11/google-announces-launch-of-google-maps_28.html

[11] Source: https://reputation.com/resources/articles/milestones-in-the-history-of-google-maps/

[12] Figure B.3 in the appendix shows the scale of downloads of Maps after it was no longer the default option for all smartphones.

[13] Source: https://www.reviewtrackers.com/reports/online-reviews-survey/

[14] My work in this section builds on other work in this area, including Shilony (1981), Neven (1986), and Fournier (2019).

$$
\begin{aligned}
s - x_a + \rho u_g + (1-\rho)u_w &= x_b - s + \rho u_w + (1-\rho)u_w \\
s &= \frac{x_a + x_b}{2} + \frac{2\rho - 1}{2}(u_g - u_w) \\
s &= \frac{x_a + x_b}{2} + \Lambda
\end{aligned}
$$

where $\Lambda = \frac{2\rho-1}{2}(u_g - u_w)$. Each firm attracts the mass of consumers which are on "their side" of s. The firms' best-response function is contingent on s, such that there are two main cases with two subcases each. For a visual treatment of these cases, see Figure B.1.

3.1 Case I: $s \le \gamma$

When $s \le \gamma$, firm a will only attract consumers from the high-density area, so their best-response will always be $x_a = \frac{s}{2}$, yielding $m_a = sH$ consumers. The mass of consumers patronizing firm b will therefore be $m_b = H(\gamma - s) + L(1-\gamma)$.

3.1.1 Subcase a: $\frac{1}{2}m_b \le H(\gamma - s)$

If less than half of firm b's consumers are found in the lower-density area, firm b will choose to locate in the high-density area, such that $H(x_b - s) = \frac{1}{2}m_b$. Therefore, $x_b = s + \frac{m_b}{2H}$. The optimal solutions are thus $x_a = \frac{1}{4H} + \Lambda$, $x_b = \frac{3}{4H} + \Lambda$, and $s = \frac{1}{2H} + 2\Lambda$.

3.1.2 Subcase b: $\frac{1}{2}m_b > H(\gamma - s)$

If more than half of firm b's consumers are in the lower-density area, x_b will also be in that area, such that $L(1 - x_b) = \frac{1}{2}m_b$, or $x_b = \gamma + \frac{m_b/2 - H(\gamma - s)}{L}$. This leads to $s = \frac{2\Lambda + \gamma + \frac{1-2H\gamma}{2L}}{\frac{3}{2} - \frac{H}{2L}}$; for simplicity, I do not rewrite x_a and x_b here.

3.2 Case II: $s > \gamma$

When $s > \gamma$, firm a attracts customers from both the high- and low-density areas. This means that firm b relies on customers only from the low-density area, such that their best response is $x_b = s + \frac{1-s}{2} = \frac{1+s}{2}$. Firm b receives $m_b = (1-s)L$ customers, so firm a receives the remainder, $m_a = \gamma H + (s - \gamma)L$.

3.2.1 Subcase a: $\frac{1}{2}m_a \le \gamma H$

If less than half of firm a's consumers are found in the higher-density area, firm a will choose to locate in the high-density area, such that $x_a H = \frac{1}{2}m_a$, or $x_a = \frac{m_a}{2H}$. Solving through yields $x_a = \frac{L}{2H}\left(\frac{(1+\gamma)H - \gamma L + 2\Lambda}{3H - L}\right) - \frac{H-L}{2H}\gamma$, $x_b = \frac{(4+\gamma)H - (1+\gamma)L + 2\Lambda}{6H - 2L}$, and $s = \frac{(1+\gamma)H - \gamma L + 2\Lambda}{3H - L}$.

3.2.2 Subcase b: $\frac{1}{2}m_a > \gamma H$

If more than half of firm a's customers are in the higher-density area, firm a will locate in the low-density area to compete more directly with firm b. Their best-response function will satisfy $(x_a - \gamma)L + \gamma H = \frac{1}{2}m_a$, or $x_a = \gamma + \frac{m_a/2 - \gamma H}{L}$. Solving through the equations yields $x_a = \frac{(3\gamma+1)L - 3\gamma H}{4L} + \Lambda$, $x_b = \frac{(3+\gamma)L - \gamma H}{4L} + \Lambda$, and $s = \frac{(1+\gamma)L - \gamma H}{2L} + 2\Lambda$.

3.3 Perfect information

When consumers gain access to the Internet, and reviews about firms a and b, that effectively gives them perfect information. Consumers can therefore tell their own type, and act accordingly. I assume that the masses of consumers who prefer firm a or firm b are distributed evenly across the continuum—in other words, for any point x, there is a ρ chance that a consumer at that point prefers firm a and a $1-\rho$ chance that she prefers b.

This effectively means that firms a and b are now optimizing over two consumer distributions simultaneously; preferences are not such that a consumer who prefers firm a will go there no matter the distance. The firms still seek to maximize their total consumer mass.

Whereas the previous descriptions only faced one midpoint, s, there will be distinct indifference points for each consumer distribution. Rather than $s = \frac{x_a+x_b}{2} + \Lambda$, if we define "type-$a$" consumers as the ρ mass that prefer firm a, then $s_a = \frac{x_a+x_b}{2} + \Lambda$ and $s_b = \frac{x_a+x_b}{2} - \Lambda$, as the $u_g - u_w$ term will shift *away* from firm a for the type-b consumers.

Because the firms are best-responding across two consumer distributions, the general decision for x_i^*, $i \in \{a, b\}$ is

$$x_i^* = \rho x_i(s_a) + (1-\rho)x_i(s_b)$$

which considers the different best-response functions given the different values for s_a and s_b. As these best-response functions depend on the cases described above, there are sixteen possible combinations of cases. As such, I have not derived closed-form solutions for all cases at this time. However, I *am* able to simulate, through iterative best-response functions, how firms respond for given values of H and γ. This allows me to describe some implications of this change in consumer information.

3.4 Implications

For simplicity, I consider the case where both firms locate on their "own" side, and at least some consumers in the low-density area continue to patronize firm a in both groups of the perfect-information realization. That is, for both values of s, I consider only case II(a).

The closed-form solution for x_a is

$$x_a = \frac{3H}{3H-L}\left[\frac{H-L}{2H}\gamma + \frac{L}{2H}(2\rho-1)\Lambda + \frac{L}{6H}(1+(2\rho-1)\Lambda)\right]$$

which is sufficient to backsolve for x_b and s_a, s_b. For a visual treatment of this case, see Figure B.2 in Appendix B.

3.4.1 Entry and exit decisions

Perfect information tends to equalize visitation closer to ρ, as the "best" option is no longer the automatic choice for all consumers in the middle. If rents remain unchanged, consumers between x_a and x_b tend to shift towards x_a at higher rates. Perfect information may therefore encourage entry in high-density areas and discourage it in low-density areas, as it becomes easier (harder) to earn a profit.

3.4.2 Chain/large-firm belonging

Suppose that u_g and u_w are generally unknown in the base case, with both being believed draws from $U(\cdot)$, a distribution with a long right tail. Large firms (such as fast-food chains or large retailers with many locations) may have previously known utilities u_{ch}, or exhibit narrower distributions. After the "realization" of these u values, establishments belonging to chains could be better or worse off. The longer the right tail of the U distribution (the larger the difference between the expected and realized quality), the more establishments that are part of large firms, whose quality is better-known, would stand to gain.

Alternatively, large firms tend to be of higher average quality than small firms. This could serve to tip the scales and reallocate more profit to such firms as in the previous subsection, as consumers learn their preferences for such firms, and become more willing to travel to patronize them.

3.4.3 Firm location choice

In this subcase environment, perfect information tends to result in firms locating closer together. However, interactions with changes in u_g and u_w, or their distributions, can also lead to firms locating further from one another. However, if it is costly for firms to relocate following an information shock, they may not do so in either direction—which means that only the balance of profits would change between firms. Figure B.2 illustrates such a scenario, and demonstrates that fixing firms' locations benefits the firm with the already-higher expected value more.

4 Data

In this section, I provide an overview of the data sources I use to test the implications from the previous section. To estimate the impact of mobile broadband on establishment-level outcomes across the United States, I use two main data sources. The first, the Reference Solutions Historical Business Data from Data Axle, contains information on all establishments in the United States from 1997 to 2024. The second is a composite dataset, created using two sources from the FCC: Form 477 reports and information from the Antenna Structure Registration (ASR) program.

4.1 Data Axle

Data Axle (formerly Infogroup, RefUSA) compiles information about U.S. businesses at the establishment level, providing a rich source of data. The company collects this information through a variety of means—business license applications, county courthouses, press releases, professional licensing requirements (such as those for lawyers or health professionals), tax filings, etc.[15] Once this information is collected, it is verified continuously. All establishments are contacted at least once per year, allowing more information to be collected, such as employment counts and annual sales volumes.[16] The result of this process is a detailed set of business addresses, latitude and longitude, industries (assigned by the compilation and verification team to NAICS and SIC codes), corporate ownership (compiled through tax records), employment counts, and more.[17]

[15] Source: `https://www.data-axle.com/marketing-solutions/library-academia/`

[16] Due to underreporting, employment counts and sales volume are frequently imputed, using proprietary algorithms. With that said, employment counts are much more frequently provided to Data Axle at the establishment level: approximately 49% of businesses provide an employment count.

[17] This data set is becoming increasingly popular; for some recent examples of the many ways it can be used, see Chevalier et al. (2022), Liu and Bardaka (2023), Van Leuven (2022), and Geron et al. (2023). To my knowledge, there is no study

The Historical Business Data contains annual snapshots of these databases compiled by Data Axle. To ensure that new entrants into a local market are the result of true entry and not of verification difficulties, I thoroughly clean the data, ensuring that establishments are appropriately matched across time.[18] To determine new entry or firm closure, I use the year of first or last observation. That is, if a firm is first recorded by Data Axle in 2005, I assume that the establishment was first opened in 2005. If the establishment is not observed after 2008, I assume that 2008 was its true last year of observation, and that the establishment closed by the time of Data Axle's compilation process in 2009.

I aggregate these establishments up into a series of 10 mile by 10 mile (square) grid cells, which is roughly 10% the size of the average county or county equivalent in the contiguous United States. In choosing a unit of observation, there is a trade-off for both large and small areas. Large areas include more businesses, and allow for more dynamic changes as the area sees potentially increased development over time, but also may be so large that measures of mobile broadband coverage obscure important local gaps in availability. Likewise, small areas can allow for more accuracy and granularity in mobile broadband coverage, but complicate inter-establishment distance metrics. The smaller an area, the fewer firms are in that area—which also means that more areas have one or no firms of a given type, rendering any distance calculation meaningless. While I vary the unit of observation as a robustness check, my primary grid-cell specification attempts to bridge the gap in size between counties and zip codes.

Figure 5 provides an example of what a grid cell looks like. Focusing in on the grid cell containing Lansing, MI, Figure 5 includes all establishments in nearby cells. In the main cell, establishments that are part of large firms (defined as having a presence in three or more states and at least 250 locations) are plotted in blue, while others are plotted in red.

4.2 Mobile broadband

The highest-quality data source for both mobile and fixed-connection broadband coverage in the United States is the Form 477 data collected by the FCC. Since December 2014, mobile broadband providers have been required to submit company coverage records through Form 477, which is then compiled into publicly-released information by the agency. By the time of this initial data collection, however, the first wave of mobile broadband rollout was well under way, and had been for nearly a decade. This means that, to determine when a location first gained access to mobile broadband in the form of 3G (or better), I must use supplementary information.

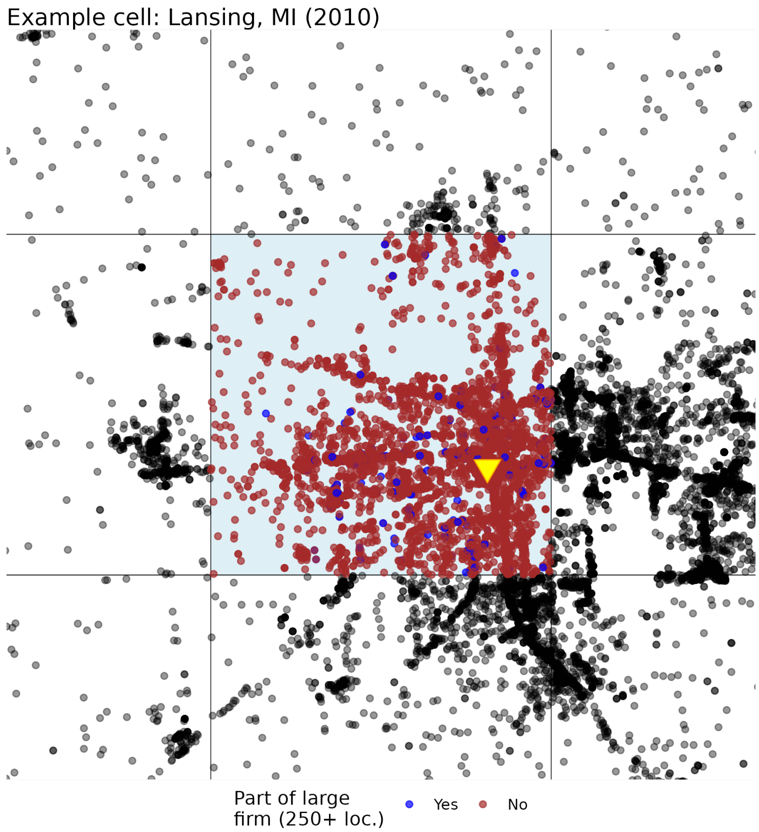
The FCC's Antenna Structure Registration (ASR) system requires entities that own an antenna structure (tower) of over 200 feet in height to file information on said tower's location, height, date of construction, and any modifications with the FCC. This allows me to use the construction of new towers, combined with information about local topography, to infer coverage in nearby areas. Thus, to estimate historical 3G coverage, I use December 2015 Form 477 reporting (shown in panel (a) of Figure 6) and periods with zero mobile broadband coverage in 2000-2004,[19] along with information on tower construction, to train a random

evaluating this dataset as compared to Census business microdata or similar, though Ramiller et al. (2024) evaluate Data Axle and Infutor *consumer* mobility records.

[18]The data contain a unique identifier for each establishment, which is consistent over time. I use this identifier, along with fuzzy-matched company names (within 2 characters of each other, and with an identical first character) to determine that an establishment in one year is the same as an establishment in another year. It is highly unlikely for two firms with similar names to open near each other (consider the possible confusion resulting from neighboring firms named "ABC Enterprises" and "ABD Enterprises"), so any small discrepancies are likely to be the result of input error. I also use latitude/longitude rounded to the third decimal point (providing an estimated precision of 110m at the equator) to further ensure that these observed establishments correspond to the same underlying business.

[19]Given that 3G was rolled out in the United States starting in around 2005, this gives me accurate data on which to fit a

Figure 5: Data Axle and grid cells



Notes: This figure depicts establishments recorded in Data Axle as of 2010 in and around the city of Lansing, MI. The state capitol building is denoted by the yellow triangle. Each grid cell is 10 miles by 10 miles. The map depicts establishments within the cell containing Lansing based on whether or not said establishments are part of a "large firm," a firm with 250 or more establishments in three or more states.

forest model to predict 3G coverage levels from 2005-2014. I emulate Hersh, B. J. Lang, and M. Lang (2022) in the variables I include in the model, largely focusing on tower-level information (height, the number of towers within 20 miles of the location) and local characteristics that may interfere with cell coverage (standard deviation of local elevation).[20]

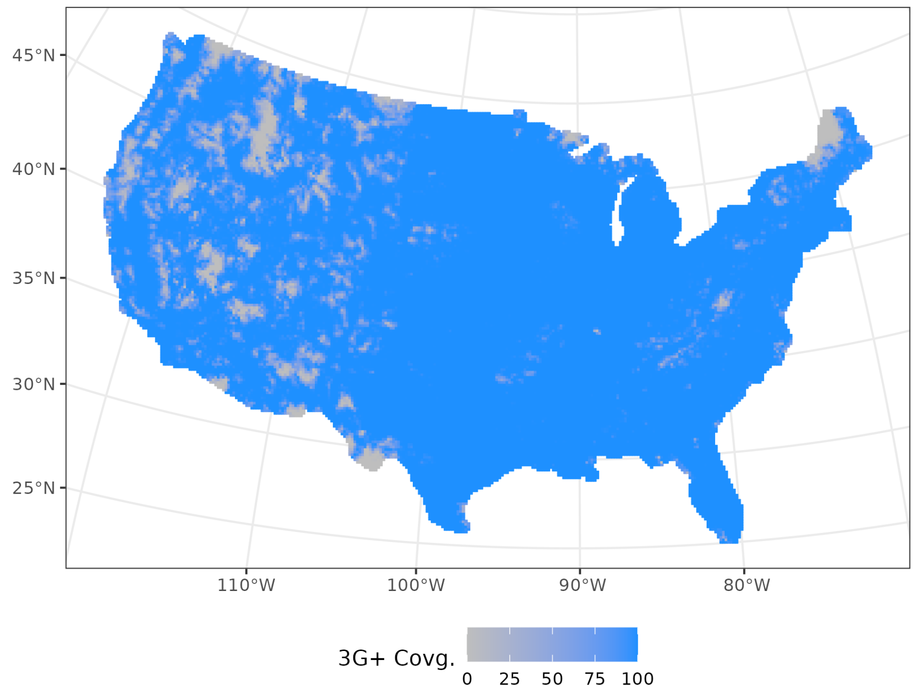
The random forest itself uses the percent (0-100) of a census block covered by some kind of mobile broadband as the outcome of interest, though I aggregate this up to the grid cell level. This means that the predicted values the model produces (likewise 0-100) can be thought of either as proportions of coverage or as probabilities of coverage. In one sense, an area with a coverage rate of 80 is 80% covered. But if we were to take a random location within this area, there is an 80% chance that that specific point would be covered. With this in mind, I employ different thresholds for an area to be considered "treated"; the most intuitive (and my preferred specification) is 50%, though I demonstrate how the estimated treatment effects may change with stricter (60%) or less strict (40%) cutoffs for broadband access.

The random forest generally behaves as expected, and matches tower construction to expansions in coverage. For some locations in the Mountain West (Montana, Utah, Colorado, etc.) the random forest

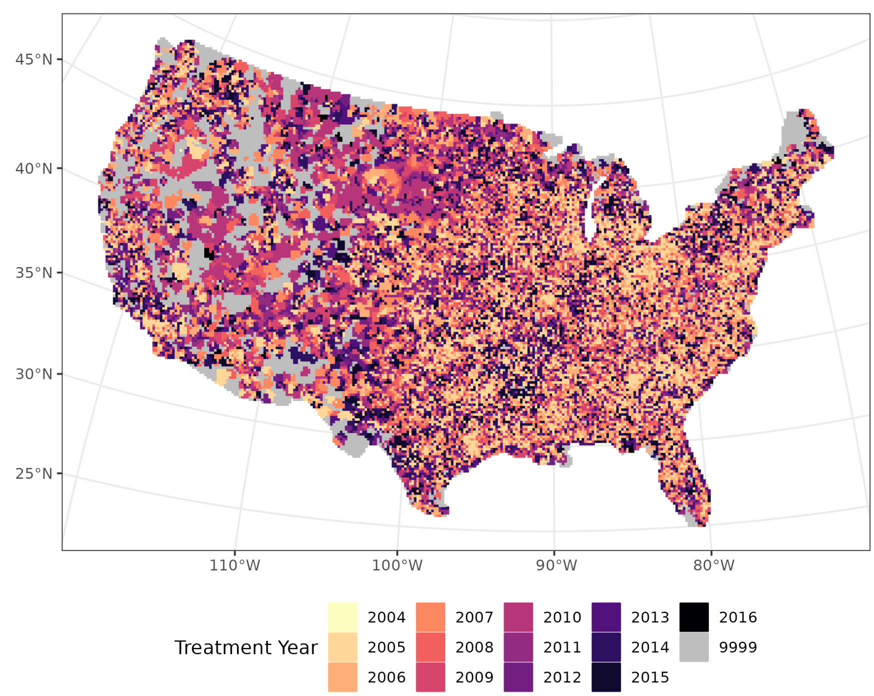
model.

[20] I source information on local topography from Amazon Web Services, accessed via the `elevatr` package in `R`.

Figure 6: Smartphone and mobile broadband adoption



(a) Observed mobile coverage, December 2015



(b) Predicted year of first coverage

Notes: Panel (a) depicts reported mobile broadband coverage as of December 2015, using the FCC's Form 477 report data. Coverage is based on 3G (or better) infrastructure, which includes 4G and 4G LTE. Panel (b) shows the estimated year of majority coverage, based on a random forest predictive model. The year indicated is the first year for which coverage meets or exceeds a threshold of 50%.

Table 1: Summary statistics

Variable	Mean	Std. Dev	Min	Max	Count
Count of all estabs.	409.5	2208.3	0	238658	617,933
Count of consumer-facing estabs.	139.309	764.771	0	85034	617,933
Count of CF expanded estabs.	237.822	1341.689	0	146047	617,933
Count of CF expanded (II) estabs.	286.102	1593.754	0	167146	617,933
Count of retail estabs.	60.976	333.712	0	38119	617,933
Count of restaurants	17.758	113.512	0	14550	617,933
Count of non-consumer estabs.	78.239	369.101	0	40159	617,933
Count of NC expanded estabs.	97.354	488.458	0	54735	617,933
Prop. all estabs. in large (250+ loc.) firm	0.018	0.046	0	1	447,853
Prop. consumer-facing estabs. in large (250+ loc.) firm	0.031	0.060	0	1	397,038
Prop. retail estabs. in large (250+ loc.) firm	0.023	0.056	0	1	363155
Prop. restaurants in large (250+ loc.) firm	0.034	0.076	0	1	286,759
Prop. non-consumer estabs. in large (250+ loc.) firm	0.011	0.054	0	1	424,534
Prop. all estabs. last $\geq$ 1 year	0.771	0.137	0	1	459,635
Prop. consumer-facing estabs. last $\geq$ 1 year	0.754	0.160	0	1	416,667
Prop. non-consumer estabs. last $\geq$ 1 year	0.768	0.159	0	1	438,473
Total Population	9,213	44,573	0	3,140,866	617,933
Unemployment Rate (%)	6.186	2.889	1.100	29.100	617,933
Minimum distance to interstate (mi)	34.821	31.493	0	189.706	617,933
3G+ coverage (2000-2004, 2015)	5.477	22.390	0	100	552,913
3G+ coverage (2000-2018, smoothed)	38.839	36.686	0	109	552,913
3G+ coverage (random forest prediction)	41.549	42.370	0	100	552,913

Notes: Author's calculations, using data from 2000-2018. "Consumer-facing" industries include NAICS codes 44-45, 52, 53, 71, and 72. The first "expanded" grouping adds codes 51, 54, and 81; the second adds 61 and 62. Non-consumer facing industries are 11, 21, 22, 23, and 31-33; the expanded version adds 42 and 55. Decisions made by the author. More information about NAICS codes can be found at `https://www.census.gov/programs-surveys/economic-census/year/2022/guidance/understanding-naics.html`.

predicts less than 50% mobile broadband coverage by 2015. However, data from the FCC confirm that some of these areas *are* covered by that time. With this in mind, I employ a specification with a mixture of annual random forest predictions and linear smoothing based on observed 2015 coverage as a robustness check.[21] Panel (b) of Figure 6 shows the resulting treatment timings across the United States.

4.3 Summary statistics

Table 1 includes summary statistics for my sample population. The average grid cell has a population of about 9,200 and includes around 410 total establishments. Around 34% of those are explicitly consumer-facing, while another 35% can be thought of as "consumer-aligned"—this includes firms in the education and health care industries, which may not respond to consumer pressures in the same way as firms in sectors like retail or food service. Among these consumer-facing establishments, around 4.79% are part of firms that have a presence in three or more states, with 250 or more locations; by this definition, large firms tend to be concentrated in these industries, as the overall rate is only 1.76%. 77% of establishments remain open the year after first entry, and 52% remain open after three years, with attrition not differing substantially by industry cluster.

[21] This mixture is half and half, though could be varied further.

5 Estimation methods

There are well-known issues with estimating an average treatment effect on the treated under staggered treatment using a two-way fixed-effects framework.[22] With this in mind, and with evidence of differential pre-trends by treatment status without covariates, I employ the difference-in-differences estimator from Callaway and Sant'Anna (2021). This estimator allows for the parallel pre-trends assumption to hold *conditional on covariates*, while also fixing weighting issues endemic to the two-way fixed-effects approach.

This gives me a main estimating equation of

$$y_{it} = \sum_{g} \sum_{t \geq g} D_{it}^{(g)} \cdot ATT(g,t) + \alpha_i + \tau_t + \varepsilon_{it}$$

where y_{it} is the outcome of interest, α_i and τ_t are (respectively) unit (grid-cell) and time (year) fixed effects, and $D_{it}^{(g)}$ is a binary variable indicating whether unit i, as part of treatment group g, is treated at time t. $ATT(g,t)$ is the average treatment effect on the treated (ATT) for group g at time t, and is calculated by performing repeated two-by-two difference-in-differences regressions. The overall average treatment effects and the event-time graphs that I present are based on aggregations of these group-time effects, whether across all groups and treated time periods (overall ATT) or across groups at a common relative time period (event-study graphs).

The $ATT(g,t)$ terms are calculated conditional on controls, and require a conditional parallel trends assumption to be valid estimates.[23] My controls are local population,[24] unemployment rate, and the cell's distance to the nearest interstate. My identifying assumption is therefore that, conditional on population, local employment, and major nearby infrastructure, business outcomes should have evolved similarly in treated and untreated areas if mobile broadband had not occurred in either location.

As for exogeneity, mobile broadband rollout decisions—such as the construction of cell towers or similar infrastructure—need to be as good as random, after controlling for local population, economic indicators, and the presence of major roadways. The literature on cell-tower site choice suggests this is reasonable, finding that firms generally focus on expansion, capacity, and quality when choosing where to locate a tower (Pflughoeft, Nemecek, and Butz, 2022).[25] Population and business centers are therefore logical starting points. Site decisions also require ensuring sufficient energy, having road access for maintenance, and adhering to local land use restrictions such as zoning. This suggests that, after choosing a general vicinity in which to build, telecommunications firms will use whichever local site best fits their requirements.

6 Results

I examine five major outcomes. All are calculated based on Data Axle information at the grid-cell level for a given year. The first two outcomes are counts of new entrants and closures.[26] Closures are associated

[22] For more details, see Goodman-Bacon (2021) and Roth et al. (2023), among others.

[23] The default Callaway and Sant'Anna (2021) approach uses a "doubly-robust" approach, consisting of inverse-probability weighting (IPW) and regression adjustment (RA). However, IPW requires an overlap assumption that does not estimate terms if certain conditions (e.g. local population) are too indicative of treatment timing. In the interest of estimating a broader range of effects, I choose to use RA alone.

[24] In my current specification, because all study areas have the same area (100 mi^2), this is equivalent to population density.

[25] "Expansion" provides coverage in areas without it; "capacity" allows for greater traffic in areas with existing coverage; and "quality" reduces call dropping or improves connectivity standards. See the paper cited above or `https://www.steelintheair.com/site-selection/` for more details.

[26] Based on the data-cleaning process outlined in Section 4.1, determining whether a firm is new or closing is determined by the year of first/last observation.

with the year following closure, so counts in 2009 include firms that were open in 2008 but not in 2009. The proportion of establishments belonging to a large firm is based on how many establishments of a given type/industry are deemed part of "large" firms. Survival rates are moving averages, based on all firms in a given sector that have operated in a cell, from 1997 (the start of my data) to the year in question. For instance, if 70% of all firms that opened from 1997-1999 were open for one or more years, the one-year survival rate across all industries in 2000 would be 0.7.[27] Finally, average distance to nearest competitor is based on within-industry distances. For each firm, I determine the nearest firm in the same industry; the value for the cell is the average of this distance. In Section 6.4, I consider the distance from new entrants to the nearest incumbent establishment, focusing on consumer-facing industries.

[27] This is because it is impossible for a firm opening in 2000 to have been open for one year by 2000.

Table 2: Count of new establishments

	All	Cons. facing	Expanded CF	Expanded CF (II)	Retail	Restaurants	Non-consumer	Expanded NC	Government
Pred. $\geq$ 40	-5.6015*	-3.1246*	-4.7170*	-3.8752*	-1.9138*	-0.4201*	-2.1455*	-3.0143*	-0.1182*
	(0.7568)	(0.2502)	(0.3921)	(0.4301)	(0.1390)	(0.0260)	(0.2334)	(0.2644)	(0.0181)
Pred. $\geq$ 50	-5.3665*	-2.7406*	-4.2528*	-3.5393*	-1.6679*	-0.4218*	-1.7915*	-2.6141*	-0.0883*
	(0.8072)	(0.3050)	(0.4258)	(0.4487)	(0.1633)	(0.0307)	(0.2256)	(0.3037)	(0.0205)
Pred. $\geq$ 60	-5.2166*	-2.8138*	-4.3324*	-3.5021*	-1.8216*	-0.4084*	-1.7881*	-2.6693*	-0.0705*
	(0.8526)	(0.3074)	(0.5125)	(0.4927)	(0.1670)	(0.0347)	(0.2745)	(0.3195)	(0.0207)
Random Year	1.9228	0.5732	1.1242	1.1939	0.2837	0.0553	0.5382	0.6467	0.0404
	(1.8292)	(0.7698)	(1.2914)	(1.1381)	(0.4548)	(0.0461)	(0.7848)	(0.9749)	(0.0234)
Sample Mean:	52.2772	16.9633	29.0646	34.5569	7.5785	1.8778	10.7427	13.0368	1.3966

Notes: All outcomes measure the count of *new* establishments of different types. Each regression uses a threshold of either 40, 50, or 60 to determine year of first treatment by mobile broadband. All regressions use the Callaway and Sant'Anna (2021) estimator, controlling for distance to nearest interstate, local population, and local unemployment rate. Asterisks indicate significance at or below the 0.05 level.

Table 3: Count of closed establishments

	All	Cons. facing	Expanded CF	Expanded CF (II)	Retail	Restaurants	Non-consumer	Expanded NC	Government
Pred. $\geq$ 40	-0.8517*	-1.6120*	-2.0568*	-1.0786*	-1.0102*	-0.1765*	-0.2190*	-0.6904*	-0.0454*
	(0.4027)	(0.1579)	(0.2684)	(0.3189)	(0.0761)	(0.0251)	(0.0965)	(0.1035)	(0.0214)
Pred. $\geq$ 50	-2.0568*	-1.8452*	-2.5265*	-1.7115*	-1.0816*	-0.2163*	-0.4076*	-0.9076*	-0.0683*
	(0.5990)	(0.1912)	(0.3398)	(0.4077)	(0.0967)	(0.0269)	(0.1063)	(0.1302)	(0.0214)
Pred. $\geq$ 60	-2.0807*	-1.8571*	-2.5449*	-1.6448*	-1.0818*	-0.2089*	-0.4906*	-1.0304*	-0.0717*
	(0.5104)	(0.1931)	(0.3342)	(0.3500)	(0.1001)	(0.0322)	(0.1071)	(0.1262)	(0.0203)
Random Year	0.5624	0.0545	0.2203	0.1926	0.0562	0.0123	0.2025	0.2886	0.0042
	(0.7341)	(0.3490)	(0.5359)	(0.6880)	(0.1143)	(0.0523)	(0.1556)	(0.2271)	(0.0240)
Sample Mean:	46.7718	15.3189	26.3738	30.6049	7.5258	1.5679	10.1453	12.6906	1.3985

Notes: All outcomes measure the count of *closed* establishments of different types. Each regression uses a threshold of either 40, 50, or 60 to determine year of first treatment by mobile broadband. All regressions use the Callaway and Sant'Anna (2021) estimator, controlling for distance to nearest interstate, local population, and local unemployment rate. Asterisks indicate significance at or below the 0.05 level.

6.1 Establishment counts

If consumer access to smartphones and virtual directories like Maps was favorable to incumbent firms, we would expect a decrease in closures, as existing firms should exit less frequently. Similarly, if the ability to advertise and be discovered on this new platform was advantageous to new entrants, we would expect an increase in entry. Because this is a shock based on consumer information, effects should be strongest for (or be restricted to) consumer-facing industries.

Table 2 shows that consumers' ability to use smartphones is associated with a decrease in both closures and new entries, and that this effect is stronger for establishments catering to consumers than other firms. In Table 2 and elsewhere, each row is the ATT calculated from a different Callaway and Sant'Anna (2021) estimation using a particular threshold for treatment determination. The first three rows use cutoffs of 40%, 50%, and 60% coverage, respectively, while the fourth employs a random treatment year as a placebo check.[28] These results demonstrate robustness to different specifications, which are expanded on in Section 6.5.

In Table 2, I observe a decrease of 5.3 new entries across all industries (around 10% of the mean). I find larger proportional changes in consumer-facing establishments overall (-2.74, 17% of mean) and subsets such as retail (-1.67, 22% of mean) and restaurants (-0.4, 22% of mean). There is also a statistically significant decrease in non-consumer industries which is similar in magnitude. Results are still significant but proportionally smaller among government-associated establishments, where we would expect no change (-0.09; 6% of mean).

While the mean number of new and exiting establishments is similar within industries, Table 3 finds smaller effects on non-consumer closures, about half the size of the reduction in new openings (4% of the mean). The reduction in consumer-facing closures remains larger and similar in magnitude to the decrease in new entrants (-1.8, 12% of mean). Together, these results appear to indicate that incumbent firms benefit. A sharper reduction in the number of new entrants than closing establishments suggests a reduction in churn, and less new/unfamiliar competition.

6.2 Survival rates

The evidence with regards to firm survival is weaker than the evidence for entry/exit changes. I therefore show these results more as supplemental evidence regarding this technology being incumbent-favoring, rather than arguing that it necessarily helps firms survive longer. Table 4 examines how the likelihood that, among all firms that were observed as operating in a given location, a given consumer-facing establishment remains open one, three, or five years after its initial entry. Using a 60% threshold, treatment is associated with a 0.2 percentage point increase in the proportion of firms that remain open one, three, or five years in the future; the more intuitive 50% threshold finds a larger effect, but is only significant in survival after three years. As suggestive evidence, this is useful, but the practical significance of this effect is quite low—74.5% of all consumer-facing establishments remain open the year after they open, 47% after three years, and 28% after five years. At most, this modest effect represents a 0.9% increase in this likelihood (looking five years ahead).

[28] This random year is weighted to follow observed treatment patterns—more early adopters than late adopters, for instance.

Table 4: Survival rates of consumer-facing firms

	Last 1+ year	Last 3+ years	Last 5+ years
Pred. $\geq$ 40	0.0018	0.0051	0.0025
	(0.0030)	(0.0052)	(0.0066)
Pred. $\geq$ 50	0.0017	0.0040*	0.0038
	(0.0014)	(0.0019)	(0.0022)
Pred. $\geq$ 60	0.0021*	0.0027*	0.0026*
	(0.0008)	(0.0010)	(0.0011)
Random Year	-0.0012	-0.0002	0.0006
	(0.0008)	(0.0010)	(0.0010)
Sample Mean:	0.7445	0.4711	0.283

Notes: All regressions in this table consider "consumer-facing" firms only. This includes NAICS 44-45, 52, 53, 71, and 72. Each regression uses a threshold of either 40, 50, or 60 to determine year of first treatment by mobile broadband. All regressions use the Callaway and Sant'Anna (2021) estimator, controlling for distance to nearest interstate, local population, and local unemployment rate. Asterisks indicate significance at or below the 0.05 level.

6.3 Large firms

The previous two subsections provided evidence regarding how incumbent firms were affected by 3G coverage, but the way that Internet directories like Google Maps work may also have helped large firms expand their foothold across consumer-facing industries. Table 5 shows that the proportion of establishments belonging to a large firm (with 250 or more locations) increased by 7-17%. I find no significant increase among industries not catering to consumers.[29,30]

A growing proportion of establishments being part of large firms indicates that such firms may be able to extract more profit than their competitors during the study period—enough to either justify opening additional locations, or to drive other firms out of business through competition. Figure 7 shows a clear trend break beginning when mobile broadband and smartphones become available, so this effect may get stronger over time.

[29] Based on my definition of "large firms," it is relatively more likely that firms in consumer-facing industries fit the description than do firms in other industries. However, even using the strict cutoff as seen in Table 5, around 4.1% of consumer-facing establishments are part of a large firm, while 0.72% of non-consumer establishments are.

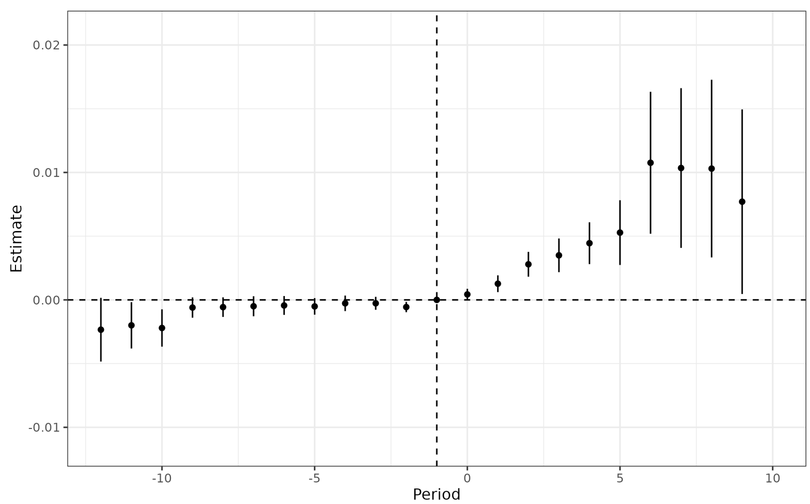
[30] Non-consumer results omitted for space.

Table 5: Proportion of establishments belonging to a large firm

	Prop. all, large	Prop. CF, large	Prop exp. CF, large	Prop exp. CF (II), large
Pred. ≥ 40	0.0034*	0.0061*	0.0025	0.0012
	(0.0012)	(0.0017)	(0.0013)	(0.0020)
Pred. ≥ 50	0.0031*	0.0052*	0.0036*	0.0032*
	(0.0007)	(0.0013)	(0.0009)	(0.0009)
Pred. ≥ 60	0.0013*	0.0022*	0.0020*	0.0015*
	(0.0004)	(0.0008)	(0.0005)	(0.0005)
Random Year	-0.0006	0.0001	-0.0006	-0.0005
	(0.0004)	(0.0007)	(0.0006)	(0.0005)
Sample Mean:	0.0175	0.0311	0.0241	0.0235

Notes: All regressions in this table use a cutoff for "large firm" membership of presence in 3+ states with 250+ establishments. Each regression uses a threshold of either 40, 50, or 60 to determine year of first treatment by mobile broadband. All regressions use the Callaway and Sant'Anna (2021) estimator, controlling for distance to nearest interstate, local population, and local unemployment rate. Asterisks indicate significance at or below the 0.05 level.

Figure 7: Event-study plot for large firms' proportion of new entrants, consumer-facing industry



Notes: This figure uses a threshold of 50 to determine year of first treatment by mobile broadband. See tables for results of other specifications. This event study considers "consumer-facing" firms only, which includes NAICS 44-45, 52, 53, 71, and 72. This and all regressions use the Callaway and Sant'Anna (2021) estimator, controlling for distance to nearest interstate, local population, and local unemployment rate. Relative time periods -15 to -13 are omitted due to noise, but skew negative.

6.4 Inter-establishment distance

Where I identify statistically significant changes in firm location decisions, they tend to be practically small. The vast majority of possible pairings—whether within a given industry group, across all firms, or considering distances between incumbent/new/closing establishments—yielded no significant difference. One possible reason for this is a lack of power, as the more specific an industry I consider, the fewer observed cells have two or more establishments in said industry from which to construct a distance measure.

However, it is feasible that there *are* no real differences in firm location decisions after broadband rollout occurs. It is costly for establishments to move, and may still be risky for firms to attempt to locate in low-traffic or otherwise undesirable locations. When considering how new entrants that are part of large

Table 6: Average distance from new entrants to nearest incumbent firm

	All	Cons. facing	Expanded CF	Expanded CF (II)
Pred. $\geq$ 40	0.0068	0.0057	0.0010	0.0003*
	(0.0087)	(0.0063)	(0.0009)	(0.0001)
Pred. $\geq$ 50	0.0135	0.0064	0.0001	0.0002*
	(0.0141)	(0.0060)	(0.0007)	(0.0001)
Pred. $\geq$ 60	0.0069	0.0017	0.0003	0.0002*
	(0.0092)	(0.0017)	(0.0004)	(0.0001)
Random Year	-0.0006	0.0004*	-0.0002	-0.0002
	(0.0004)	(0.0002)	(0.0006)	(0.0005)
Sample Mean:	0.011	0.0115	0.0098	0.0094

Notes: Each outcome is the mean difference between new and incumbent (open for 3+ years) establishments within a grid cell. All regressions in this table use a cutoff for "large firm" membership of presence in 3+ states with 250+ establishments. Each regression uses a threshold of either 40, 50, or 60 to determine year of first treatment by mobile broadband. All regressions use the Callaway and Sant'Anna (2021) estimator, controlling for distance to nearest interstate, local population, and local unemployment rate. Asterisks indicate significance at or below the 0.05 level.

firms choose to locate relative to incumbents, I only find statistically significant results in consumer-facing industries in the broadest category, and even then, the effect I estimate is about a one-foot (0.0002 miles) change. Broadening the analysis to include all firms' distance from nearby establishments (which is larger, as this includes more rural areas), the most charitable change I can construct rules out any change in average location distance greater than 217 feet (0.04 miles). These recorded changes are so small so as to be practically insignificant.

In general, there appears to be no systematic change in firm location choice due to this technology, and I can reject any large changes (whether proportionally or in absolute magnitude) as implausible. Thus, it seems that the importance of location is relatively unaffected by changes in competition for prominence in other ways.

6.5 Robustness

To ensure that my results are robust, Tables 2-6 already include three different cutoffs, allowing the period of first treatment to be determined by the first year a grid cell was 40%, 50%, or 60% covered by mobile broadband. They also include a placebo check, the results of a regression using a random year of first treatment.

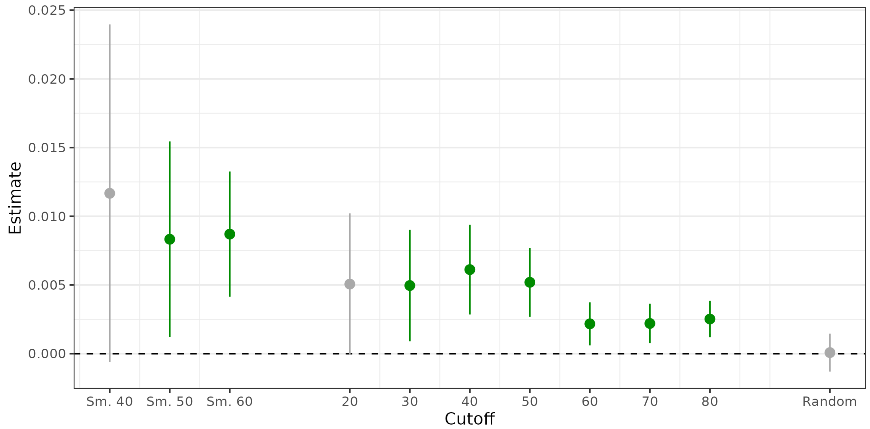
To go further, and explore potential dose-response relationships based on higher or lower coverage rates, Figure 8 employs more extreme thresholds—ranging from 20% to 80% coverage—while also considering the "smoothed" treatment level derived from a combination of random-forest predictions and linear smoothing from 2005 to 2015.[31]

Panel (a) of Figure 8 shows results from different regressions of the proportion of consumer-facing establishments that are part of large firms. For most treatment cutoffs, there is a significant and positive effect, though the size varies somewhat, and seems to decrease after about the 50% mark. This suggests that initial, early coverage may be quite important for large firms.

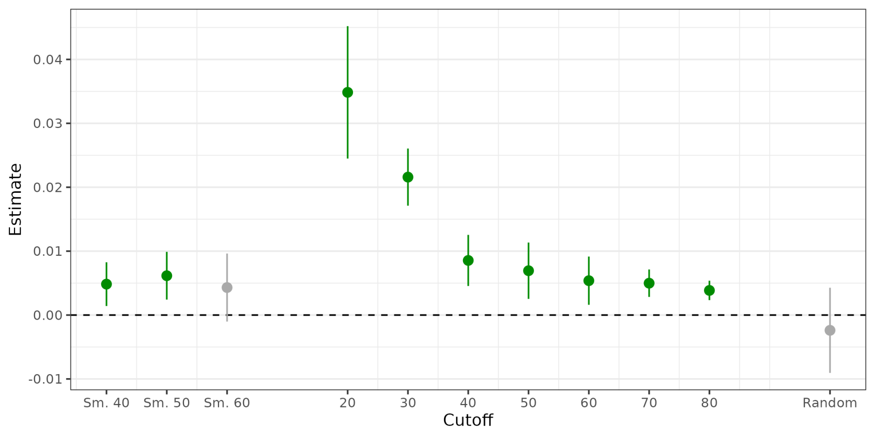
While I use 100 sq. mi. grid cells for my primary results, I also vary my unit of analysis. Counties may

[31] This ensures that all locations that should be covered by 2015 are covered; for more details, see Section 4.2

Figure 8: Consumer-facing large-firm belonging



(a) Cell level



(b) County level

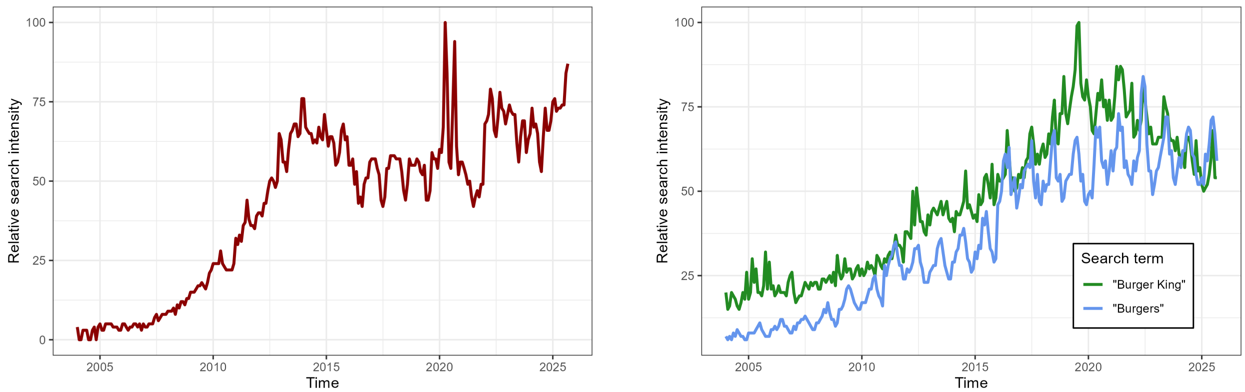
Notes: All regressions use the Callaway and Sant'Anna (2021) estimator, controlling for distance to nearest interstate, local population, and local unemployment rate. The outcome of interest for all regressions is the proportion of establishments belonging to a large firm; see column two of Table 7. Panel (a) examines this outcome at the 10-mile by 10-mile cell level, and panel (b) at the county level.Color indicates significance at or below the 0.05 level.

seem like a natural choice, as they are predefined geographic units that contain a great deal of economic activity. However, counties can be heterogeneous in undesirable ways; Los Angeles county in California, for instance, had a population in 2023 that was higher than 40 of the 50 U.S. states. Using larger geographic areas to determine "treated" status is also less desirable, as mobile coverage is often a highly local phenomenon, especially in areas with mountains or similar features that would block signal. Even so, panel (b) of Figure 8 varies my unit of analysis, using counties instead of grid cells. It shows an even higher response using low cutoffs rather than high ones, further supporting the importance of early coverage.

More generally, my results tend to be robust to this change in unit. Appendix tables A.1-A.4[32] tend to find qualitatively similar effects as my main results, though often smaller—openings and closures each seem to be affected only about half as much (proportionally). The effect on large firms' share of establishments remains similar in magnitude.

[32] I do not currently include an equivalent to Table 6, but the "random" treatment timing is statistically significant in three of four specifications—another nail in the coffin for any kind of change in location.

Figure 9: Relative interest in indexing, brands



(a) Searches for "How to get on Google"

(b) Searches for "Burger King" vs. "Burgers"

Notes: Both panels use data from Google Trends (accessed in September 2025) to show trends over time for interest in particular topics. Panel (a) shows the increase in interest for "how to get on Google," suggesting that the value of appearing in search results may be increasing over time. Panel (b) shows that, for the vast majority of 2004-2025, "Burger King" has been a more popular search term than "burgers," which may be indicative of how consumers find businesses to patronize.

7 Discussion

Together, the results examining new and closing establishments, large firm proportion, and firm survival suggest that smartphone access favors incumbent and large firms.

One potential mechanism for this result is in the way the Internet functions. In compiling lists of businesses, companies like Google need to ensure that existing establishments are listed, particularly establishments that are part of large firms. While it would reflect poorly on a directory aggregator to miss entries for local businesses, it becomes a significantly bigger problem if there is no entry for the local Walmart. Such an oversight would reflect poorly on the directory service itself, and could lead consumers to look elsewhere—certainly not what the virtual directory provider wants!

On the other hand, when consumers begin to use their smartphones rather than the local yellow pages to find businesses, local entrepreneurs then need to ensure that they are listed in the services their consumer base is using. This extra hurdle to jump through could raise the cost of opening a business, and panel (a) of Figure 9 reflects increased interest over time in "how to get on Google." However, this cost would not be the same by firm size—ensuring that a new branch location has an online presence is less costly than creating something new. This difference in relative cost likewise favors large firms.

Alternatively, services like Google (whether a consumer is looking for a business or not) want to show users what they want to see. This means that, while consumers may look for general categories like "restaurants," it becomes relatively easier for them to search for particular establishments instead. This means that consumers may be seeking out familiar, large firms, because they can more easily remember them. To that end, panel (b) of Figure 9 demonstrates that, across time, consumers search for "Burger King" at higher rates than they do for "burgers."

To briefly touch on another effect, given that it seems firms do not change their location choice given the information shock to consumers, the theoretical model in Section 3 indicates that perfect information (through a "virtual directory" like Maps) favors the generally-better, "downtown" firm at x_a, by shifting a larger portion of the consumer base in their direction after preferences become known. This means that relocation is an important margin by which the firm in the less-dense area, x_b, is able to improve their circumstances. Without that margin, such firms are squeezed out of the market—another mechanism that could explain the aftermath of broadband access.

In conclusion, prominence is valuable to firms, though the changes to consumer search caused by smartphone access have not been examined until now. I leverage an underutilized data set and machine learning, alongside modern difference-in-differences techniques, to understand how smartphone access changed the way that establishments compete with one another. I find that this new technology, which may change firms' strategies to become prominent in the minds of prospective customers, favored firms that were prominent in the pre-period. In particular, treated areas experience fewer new openings and closures, and firms in such areas tend to be somewhat more likely to remain open one or three years after opening. Perhaps due to the high potential costs associated with firm movement or new construction, I find no effect on how establishments choose to locate with respect to one another—competitors are getting no further apart nor closer together.

The impact that smartphones have had on modern life is broad, but understudied, especially within economics. I hope that this paper serves as a jumping-off point for future work on smartphones' effects on consumers, not simply how they reflect consumers' realized preferences.

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A Robustness appendix

Table A.1: Count of new establishments, county

	All	Cons. facing	Expanded CF	Expanded CF (II)	Retail	Restaurants	Non-consumer	Expanded NC	Government
Pred. $\geq$ 40	-25.8708*	-11.5292*	-18.9616*	-14.4172*	-7.3009*	-2.5629*	-8.0919*	-12.1689*	0.7815
	(8.6755)	(3.3007)	(4.8259)	(5.0455)	(1.7118)	(0.6565)	(2.5344)	(2.8190)	(0.5310)
Pred. $\geq$ 50	-32.2358*	-11.6645*	-20.2458*	-18.9658*	-6.1232*	-2.6406*	-4.4166	-6.8395	0.7456
	(8.6581)	(3.3832)	(5.5625)	(5.8505)	(2.1291)	(0.6339)	(3.4608)	(4.7113)	(0.4503)
Pred. $\geq$ 60	-16.7404	-6.8363	-11.4323	-9.4107	-4.9428*	-1.8434*	-1.5581	-3.9552	1.0163*
	(12.4530)	(4.4125)	(7.1030)	(6.7157)	(2.0309)	(0.5006)	(4.1446)	(4.9700)	(0.3963)
Random Year	9.0642	4.8396	7.4380	6.0637	2.4085	0.6583	-3.2898	-2.0536	0.1848
	(23.1812)	(9.3138)	(16.1698)	(13.0156)	(5.5159)	(0.9023)	(7.3769)	(9.2275)	(0.4455)
Sample Mean:	497.4546	163.5789	278.4039	330.792	72.9572	18.3721	105.8184	126.5652	14.0441

Notes: All outcomes measure the count of *new* establishments of different types. Each regression uses a threshold of either 40, 50, or 60 to determine year of first treatment by mobile broadband. All regressions use the Callaway and Sant'Anna (2021) estimator, controlling for distance to nearest interstate, local population, and local unemployment rate. Asterisks indicate significance at or below the 0.05 level.

Table A.2: Count of closed establishments, county

	All	Cons. facing	Expanded CF	Expanded CF (II)	Retail	Restaurants	Non-consumer	Expanded NC	Government
Pred. $\geq$ 40	-25.4391*	-14.7101*	-20.0459*	-17.2959*	-7.4640*	-1.6660*	-5.3835*	-7.9409*	-1.3668*
	(8.3021)	(4.4664)	(5.6741)	(5.9822)	(2.1748)	(0.5113)	(2.1963)	(2.7930)	(0.6142)
Pred. $\geq$ 50	-16.8627	-7.5571	-10.6468	-10.2015	-2.6917	-2.3500*	-2.0165	-4.2352	-1.3481*
	(10.1982)	(6.0529)	(8.3995)	(7.0382)	(3.7818)	(0.8038)	(3.1306)	(3.9909)	(0.3658)
Pred. $\geq$ 60	-26.1731	-10.0544*	-15.5446*	-15.3464	-4.8308*	-2.0702*	-5.1539	-7.3886	-1.1034*
	(15.1836)	(4.0671)	(6.8621)	(8.2390)	(1.9577)	(0.7024)	(4.9388)	(5.0291)	(0.3460)
Random Year	-4.8584	0.5907	-2.2992	-2.3148	-1.4002	1.8181	-1.0544	-2.1028	0.1531
	(16.1147)	(5.8763)	(8.8453)	(9.3495)	(2.4291)	(1.4115)	(5.9179)	(6.7979)	(0.3678)
Sample Mean:	436.1131	143.6989	247.1684	284.707	71.8417	15.291	97.323	120.3692	12.6265

Notes: All outcomes measure the count of *closed* establishments of different types. Each regression uses a threshold of either 40, 50, or 60 to determine year of first treatment by mobile broadband. All regressions use the Callaway and Sant'Anna (2021) estimator, controlling for distance to nearest interstate, local population, and local unemployment rate. Asterisks indicate significance at or below the 0.05 level.

Table A.3: Survival rates of consumer-facing firms, county

	Last 1+ year	Last 3+ years	Last 5+ years
Pred. $\geq$ 40	0.0026	-0.0104	0.0001
	(0.0044)	(0.0083)	(0.0043)
Pred. $\geq$ 50	0.0048*	0.0012	0.0011
	(0.0020)	(0.0032)	(0.0034)
Pred. $\geq$ 60	0.0021	-0.0008	0.0008
	(0.0021)	(0.0016)	(0.0016)
Random Year	0.0007	-0.0027	-0.0023
	(0.0016)	(0.0027)	(0.0024)
Sample Mean:	0.7593	0.4866	0.2775

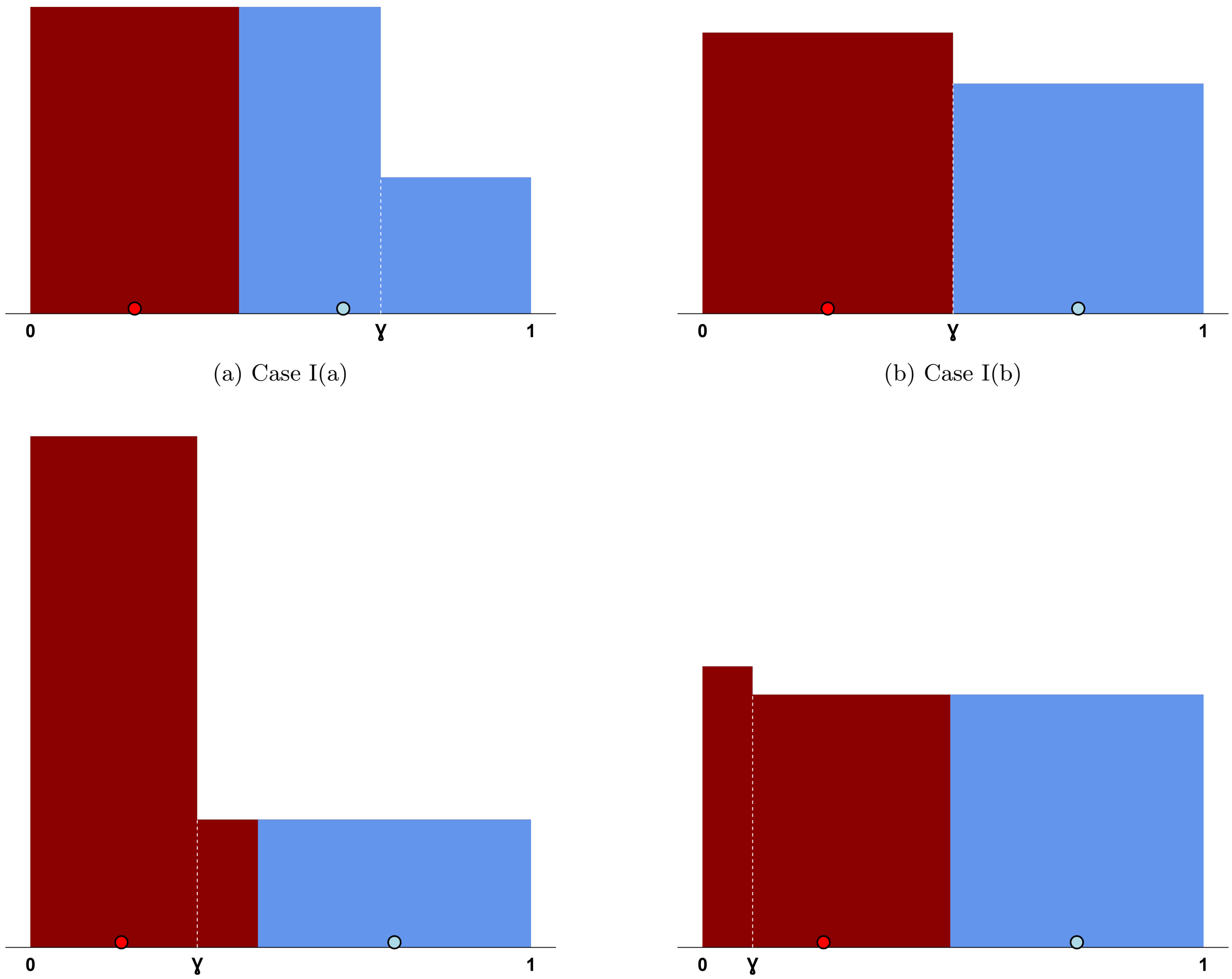
Notes: All regressions in this table consider "consumer-facing" firms only. This includes NAICS 44-45, 52, 53, 71, and 72. Each regression uses a threshold of either 40, 50, or 60 to determine year of first treatment by mobile broadband. All regressions use the Callaway and Sant'Anna (2021) estimator, controlling for distance to nearest interstate, local population, and local unemployment rate. Asterisks indicate significance at or below the 0.05 level.

Table A.4: Proportion of establishments belonging to a large firm, county

	Prop. all, large	Prop. CF, large	Prop exp. CF, large	Prop exp. CF (II), large
Pred. $\geq$ 40	0.0023	0.0085*	0.0044*	0.0020
	(0.0016)	(0.0020)	(0.0016)	(0.0022)
Pred. $\geq$ 50	0.0031*	0.0069*	0.0038*	0.0024
	(0.0011)	(0.0022)	(0.0014)	(0.0015)
Pred. $\geq$ 60	0.0028*	0.0054*	0.0031*	0.0021*
	(0.0008)	(0.0019)	(0.0011)	(0.0010)
Random Year	-0.0001	-0.0024	-0.0008	-0.0004
	(0.0012)	(0.0034)	(0.0020)	(0.0016)
Sample Mean:	0.023	0.0424	0.0316	0.0308

Notes: All regressions in this table use a cutoff for "large firm" membership of presence in 3+ states with 250+ establishments. Each regression uses a threshold of either 40, 50, or 60 to determine year of first treatment by mobile broadband. All regressions use the Callaway and Sant'Anna (2021) estimator, controlling for distance to nearest interstate, local population, and local unemployment rate. Asterisks indicate significance at or below the 0.05 level.

B Supplemental figures



(a) Case I(a)

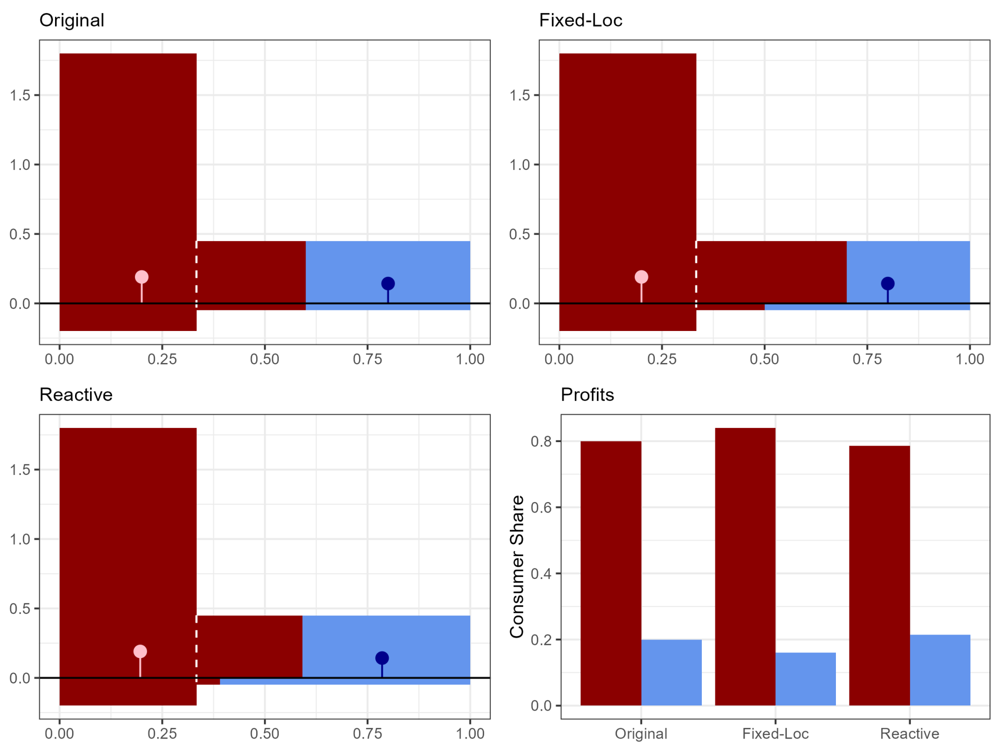
(b) Case I(b)

(c) Case II(a)

(d) Case II(b)

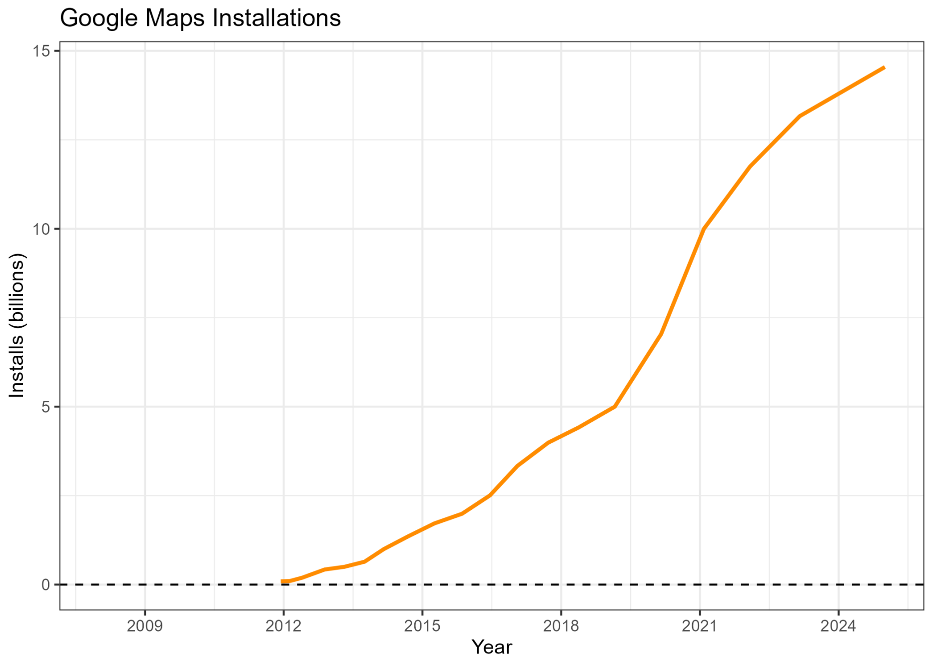
Figure B.1: Case and subcase visual examples

Figure B.2: Theoretical implication example



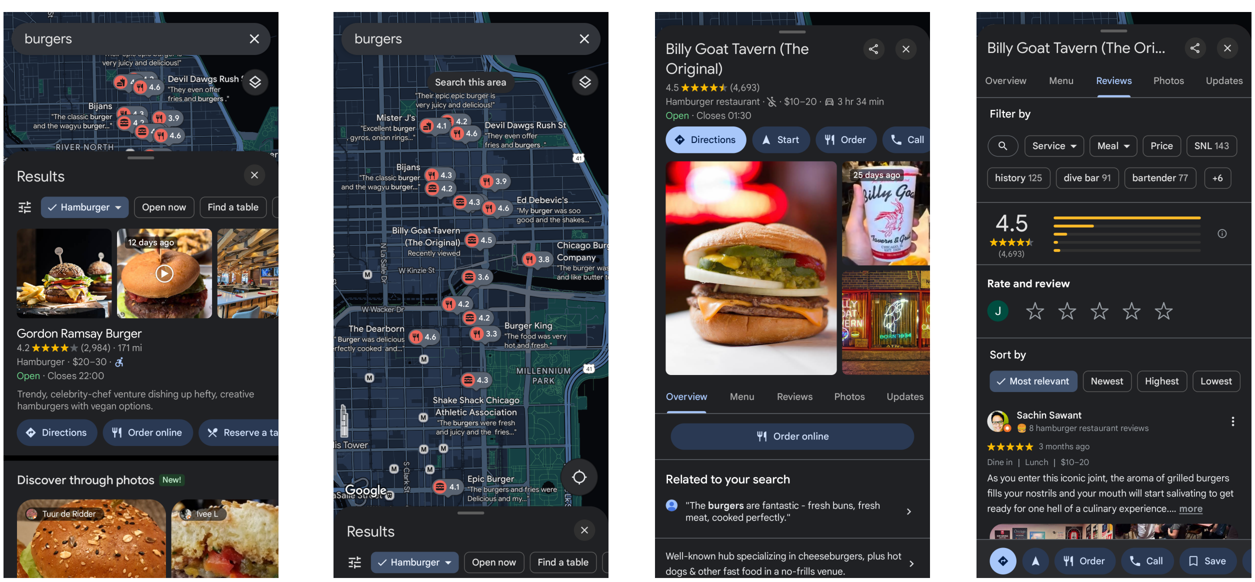
Notes: This figure demonstrates how changes in information affect the distribution of profits for the theoretical model outlined in Section 3. In this example, $H = 2$, $\gamma = \frac{1}{3}$. $(u_g, u_w) = (1.00, 0.75)$ and $\rho = 0.9$. The ρ consumers that prefer firm a are located above the zero line, while the remaining $1 - \rho$ are located below it. As consumer share sums to one, m_a in the base case (without perfect information) is 0.8, which increases to 0.84 in the fixed-location case. With reactive location choice, m_a falls to 0.785.

Figure B.3: Google Maps installations over time



Notes: This figure depicts the count of estimated installation of Google Maps over time. The data come from AndroidRank, last accessed in March 2025.

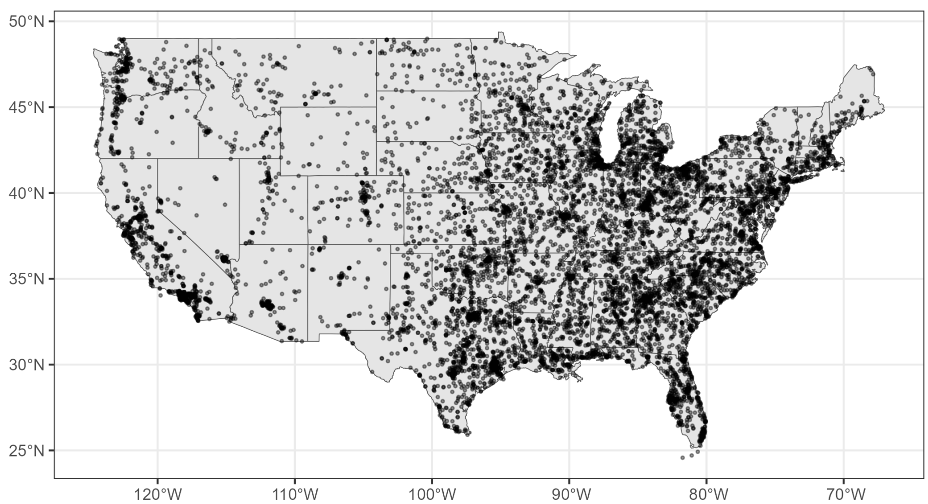
Figure B.4: The Google Maps user interface



(a) Search (b) Results (c) Establishment (d) Reviews

Notes: This figure demonstrates what a modern interface for Google Maps looks like. Screenshots taken on December 5, 2024.

Figure B.5: Antenna Structure Registration (ASR) tower locations



Notes: This figure depicts a 10% sample of all towers recorded in the FCC's Antenna Structure Registration (ASR) data in 2010.