Reshaping the Local Marketplace: Brands, Local Stores, and COVID

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December 4, 2020

Preliminary: Please check with the authors for the latest version.

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ABSTRACT

Using weekly establishment-level near real-time foot-traffic data, we show that the collapse and reallocation of foot traffic during the COVID-19 pandemic affected pharmacies across localities across the U.S. disparately. Our evidence suggests a that the COVID shock reshuffled foot traffic from independent stores to the national brands. This change occurred broadly and persisted after the initial demand shock. While government PPP subsidies and the presence of small-business-friendly banks temporarily softened the immediate shock for independent pharmacies the effect dissipated over time. The outcomes at the end of our sample period are consistent with the hypothesis that brand chains are the more productive than independents and that they were able to gain relatively more customers as COVID scrambled demand. Brand stores are initially larger, they are in more customer-dense locations, and they are in higher income areas. These characteristics are also predict competitive outcomes of brand stores relative to independents. Thus, the COVID shock has accelerated the ongoing rise of brands and the decline of independent pharmacies. If generalized across other markets, this change will have large implications for small businesses and the shape of local communities.

1 Introduction

COVID-19 and the resultant consumer and government responses have rocked our economy and changed consumption patterns. For small businesses in retail and personal services, the pandemic has brought about three separate shocks. There has been a general decline in foot-traffic. There has also been a reallocation in demand as customers shop in outlets closer to their homes, with declines hitting some communities harder than others. These changes have delivered a jolt to local marketplaces, where businesses of different sizes, complexities, and financial resources compete. Given the importance of these small businesses to the character of local communities and for job-creation, a key objective of policy over this period has been to provide them with financial assistance, which was in this instance delivered through the banking system.[1]

The shocks to small businesses have taken place against a background of competitive stress from what Hsieh and Rossi-Hansberg (2020) have characterized as an industrial revolution in services. Advances in new technologies now allow large brands to compete with small stores more efficiently across many locations. Smith and Ocampo (2020) chart the rise of large multi-establishment stores across U.S. retailing over the last two decades. In this context, there is particular concern that the demand shifts brought about by the pandemic may be breaking established consumption patterns and shifting demand to locations where national brands can gain a greater share of the marketplace.[2]

In this paper, we ask three questions: How badly have small retail bricks and mortar businesses been hit? What effect do these shocks have on the competitive struggle between large scale brands and small business providers? How well did government assistance and the banking sector help small businesses deal with the initial shock and the competition from brands? Using Safegraph establishment-level mobility data that gives us near real-time measures of foot-traffic in retail establishments, Nielsen data on consumer preferences,

[1] These concerns are not limited to the United States. In Britain, where one city, London, generates a disproportionate amount of economic activity, the issues are very stark: "For high-street businesses in big cities, the loss of commuters is a disaster....But London's loss is a boon for the commuter towns near it." (COVID-19 and the end of commuterland, *The Economist* Sept. 12, 2020. and "London Offices Aren't Filling Fast Enough for Shops Relying on Them," *New York Times*, Sept. 10, 2020.

[2] "The coronavirus will radically reshape Main Streets across the country, accelerating changes long in the making – chain stores will replace mom-and-pop businesses ...The pandemic will exacerbate what were two key trends in our lifetime: consolidation and inequality," "The end of small business." *Washington Post*, July 9, 2020.

and Census Bureau administrative data at zip code and Census block level, we examine how the COVID-19 shock changed the pattern of activity in independent stores and brand name stores across different localities. In this draft of the paper, we focus on pharmacies since it is straightforward to identify the leading national brands and because pharmacies remained open throughout the pandemic. Our sample covers 27,820 stores in 11,711 unique zip code from 2,643 counties in all 50 states and the District of Columbia.[3] We examine the role of the government's Paycheck Protection Program(PPP) and the presence of small-business friendly banks. Our granular data enables us to analyze foot traffic changes as stores in different localities were differentially affected by COVID-19 infection rates and demand shocks.

We find large declines in foot-traffic and increases in closures across all localities coincident with COVID-19 shock. Comparing independent pharmacies and large national brands and controlling for zip-week effects, we find that foot traffic almost uniformly falls more and closures increase in independent pharmacies than in pharmacies owned by national brands. The effects were accompanied by changes in clientele: we find that the average distance from home to store fell more and time in store increased more for customers of brand stores. Large independent pharmacies are particularly hard hit, especially in low-income areas and urban areas. The shock, both in the magnitude of the demand drop and the gain in the brands' relative advantage, is greatest early in the pandemic. Gains by the brands partially revert in May and do not change much for the remainder of the sample period.

Relative market share losses and closures of independent stores vary across locations. The move towards brands is largest in high-income areas. It is particularly strong in the suburbs, is weaker in urban and rural areas, and reverses in business districts. Independent stores do better in zip codes where consumers score high on preference for shopping locally, and worse in zip codes where residents report shopping more frequently on Amazon.

The U.S. Federal government created subsidized program to respond to financial shortfalls to individuals and businesses caused by the COVID shocks. The principal government program to aid small businesses, the PPP loan program, was instituted in April 2020, and

[3]SafeGraph data measures changes in foot traffic at over 6 million locations in near real-time. Analysis of other local retail and service markets is in progress and will be available shortly.

the loans were disbursed by early May.[4] The PPP loans allowed businesses to pay their employees, pay mortgages, rent, or similar necessary business expenses. The PPP loans were forgivable, providing that the store does not lay off workers or substantially lower wages.

We find that the amount of PPP causes the foot traffic and the closure rate differential between the brand and independent pharmacies to shrink initially. This indicates that the cash infusion from the PPP helped independent pharmacies compete with brand pharmacies. However, the economic effect is relatively modest and is at first associated with the recovery of about 10 percent of the gain by brand stores relative to independents, but then declines and even reverses.

We also examine the role of banking at the zip-level on the outcomes for independent firms. Specifically, we examine whether the market share of banks that have issued more small business loans in the past predicts better outcomes for independent stores compared to brand stores. The fact that the banks are large relative to the zip substantially alleviates endogeneity issues. We find a positive effect in that the presence close-by of banks that engage in substantial small business lending predicts relatively better outcomes for independent stores. The effect is economically moderate, and like the PPP, diminishes for both market shares and closures over our sample period.

To summarize, the COVID-19 shock shuffled retail demand across localities. Independent pharmacies initially suffered large losses in foot traffic per store and increases in closure rates compared to brand stores. These relative losses reversed only partially over time and stabilized at about 30% more loss of foot traffic and closure rates in the period May to October[5]. PPP and the presence of small firm friendly banks partially offset foot traffic per store and closure rate losses during the period of the initial shock, but are not associated with better outcomes in the remainder of the sample period. These results suggest that the lasting effects of the COVID shock are not due to the initial shock, but to the ability of brands to secure a larger share of the foot traffic following the relocation of demand as consumers sheltered at home from the pandemic. Next, we investigate some

[4] See Chetty et al. (2020a). Bartik et al. (2020b) and Granja et al. (2020) provide a detailed description of the PPP.

[5] Independent stores have an average loss of 30% in foot traffic and a 10% in closure.

potential explanations.

We first investigate whether brands had pandemic-specific advantages over independents over the sample period. One potential advantage might be a better supply chain during a period of potential shortages. Consistent with this conjecture, we do find that brand stores closer to their warehouses, and brand stores sharing their closest warehouse with fewer other brand stores gained more foot traffic initially. However, this effect dissipated over time and does not explain the persistent gains by brand stores.

Another possibility was that independent pharmacies might be co-located with medical practices and, therefore, more sensitive to the drop in outpatient medical visits during the pandemic (Patel et al. (2020)). While do find that all pharmacies co-located within 100 or 200 yards of a medical facility or office experience larger drops in foot traffic early in the pandemic there, is very little evidence that this affects the relative outcomes of brands and independent stores.

We also examine two activities directly related to COVID at brand stores: the opening of a COVID testing facility and the presence of on-site medical clinics. On-site clinics do not predict changes in foot-traffic during our sample period significantly. On-site testing initiation does increase foot traffic beyond the pure brand effect at a store significantly, but controlling for testing sites does not change our results.

More broadly, it may be that brand pharmacies may have advantages that position them to take advantage of the COVID shock. Oberfield et al. (2020) argue that productive multi-establishment firms, such as pharmacy chains, locate their establishments in more customer-dense locations and operate larger establishments than single establishment firms.[6] We investigate whether these predicted locational characteristics also predict better outcomes during the pandemic.

Consistent with the Oberfield et al. (2020) model, we find that brand pharmacies are on average larger than independent pharmacies and that their pre-COVID retail foot traffic is higher in neighborhoods of 200 and 500 yards around brand pharmacies than around independent pharmacies. Consistent with the model, larger brand pharmacies outperform

[6] In their model these effects arise because they face different coordination costs than single-establishment firms and therefore have a different cost structure.

large independent stores over the sample period.

Taken together, our evidence suggests that the COVID shock reshuffled foot traffic from independent stores to the national brands. This change occurred broadly and persisted after the initial demand shock. The relative success of brands cannot be explained by short-term factors such as the supply-chain advantages of brands and the initiation of COVID testing at some brand pharmacies. While government PPP subsidies and the presence of small-business-friendly banks temporarily softened the immediate shock for independent pharmacies, the effect dissipated over time. The outcomes at the end of our sample period are consistent with the hypothesis that brand chains are more productive than independents and that they were able to gain relatively more customers as COVID scrambled demand. Consistent with the Oberfield et al. (2020) model of productive multi-establishment firms, brand stores were initially larger, in more customer-dense locations, and in higher-income areas. These characteristics also predict the competitive outcomes of brand stores relative to independents. Thus, the COVID shock has accelerated the rise of brands and the decline of independent pharmacies. If generalized across other markets, this change will have large implications for small businesses and the shape of local communities.[7]

Our paper builds upon several strands of work. The role of small businesses in economic dynamism and job creation and warning of the effects of declining small firms formation over time has attracted a great deal of scholarly study. Much of this work is summarized in Hurst and Pugsley (2011) and Decker et al. (2014). Karahan, Pugsley, and Sahin (2016) point out the implications of this drop for long-run business composition. Our results suggest that the COVID pandemic has hurt small independent firms both absolutely and relatively. The areas where independent firms were strong, such as business districts, have been the hardest hit and will be negatively affected by any persistent increases in working from home.

More recently, attention has been focused on the competition between national chains and small independent businesses in services and retailing. Hsieh and Rossi-Hansberg (2020) argue that technological developments have given brands a comparative advantage. Using the U.S. Census of Retailing, Smith and Ocampo (2020) characterize the rise of multi-

[7] In ongoing work we are extending this analysis to other retail and service sectors to determine how prevalent and general this trend is likely to be.

market firms between 1997 and 2003 as they move into more locations previously served by independent firms. Our paper places these developments in the context of geography and argues that the reallocation related to COVID will speed up this process.

The effect of organizational structure in competition in retailing has been studied in a different context by Chevalier (1995) and Khanna and Tice (2003, 2001). These papers analyze the strategic responses of local grocery chains to the insurgence of a more skilled national chain into their territory. We analyze the effect of a demand shock on independent stores competing with more skilled national chains across the country and the effects of the local banking environment and government financing on the equilibrium.

Several papers have examined the effects of PPP and on-demand and small business outcomes. Bartik et al. (2020a) report on how small businesses perceived financing during the COVID shock and Bartik et al.(2020b) analyze the effect of PPP on small businesses in general using survey data. Chetty et al.(2020) also use Safegraph data to analyze how COVID-19 and stabilization policies affect spending and employment. Granja et al.(2020) also analyze the effect of PPP using SBA data. These papers do not focus on person-to-person businesses, do not break out geographic characteristics, nor do they analyze the differential effect on national brands and small businesses within specific markets. We show that while the PPP was helpful to small firms, it has so far had a minor effect on their loss of market share to brands and the effect differs by geographic characteristics.

Our work also builds on the large literature on the effects of local banks on businesses. Among papers that have addressed explored this issue are Black and Strahan (2002), Cetorelli and Strahan (2006), Gilje (2019), Guiso et al.(2004) and Kerr and Nanda (2009). Several papers (Agarwal and Hauwald (2010), Nguyen (2019), Laderman (2008), and Amel and Brevoort (2005), among others) find that most small businesses borrow from nearby bank branches. Consistent with this literature, we show that the presence of small business-friendly banks in the same zip code facilitates market share retention by small firms in the COVID shock. However, this effect is relatively minor.

2 Data

We construct our sample using data from SafeGraph. SafeGraph collects information on almost 45 million cellphone users — about 10 percent of devices in the U.S.— and compiles a panel for about 6 million "points of interest" (POIs). For each POI, it provides information on the business name, physical address, and industry. If the POI belongs to a brand that SafeGraph has explicitly identified, it also provides information about the brand. SafeGraph provides a panel of weekly information for each POI about the number of visits, the distance traveled by customers from home, and time spent in the store. In this paper, we focus on business establishments of pharmacies and drug stores (NAICS code 446110) which were allowed to remain open throughout the pandemic as an essential business. We select stores in SafeGraph that recorded at least 10 visits in January 2020 to make measurement manageable .[8] To minimize the measurement error, we drop stores that share the same street address as other businesses (for example, in high-rise buildings, grocery stores, or supermarkets). In our final sample, we have 27,820 stores in 11,711 unique zip codes from 2,643 counties in all 50 states and the District of Columbia in the U.S. We construct a weekly panel of the number of visits to each store. Our sample covers the period between January 6, 2020 and October 19, 2020. For each week, we calculate changes in visits from the same month last year in log difference. Figure 1 presents the distribution of pharmacies and drug stores in our sample at the county level, together with the percentage of brand stores.

Figure 1: [INSERT FIGURE HERE]

The exposure to the COVID pandemic varied greatly by counties and states in terms of government actions. We use information provided by the New York Times to track states' policies overtime, and separate our sample period into three segments – before the stay-home mandate (SAH=0), during the stay-at-home mandate (SAH=1), and after the state announced to reopen (SAH=2).[9] For states that did not issue statewide stay-at-home orders, we code the variable equal to zero throughout. We collect zip code level

[8]SafeGraph reports that their algorithm records approximately 10% of all visits.

[9]https://www.nytimes.com/interactive/2020/us/states-reopen-map-coronavirus.html

information from several databases from the Census Bureau. We use the American Community Survey (ACS) to obtain demographic data, including population, the number of households, median household income, race groups, and education levels. We use the Zip Business Patterns (ZBP) to get information on the number of business establishments and employment, both at the industry and in total, for the zip code. We identify business districts (D_BDistrict) as zip codes that have the ratio of business employment to residential population greater than two. About two percent of all zip codes in our sample are business districts based on this definition.

We use the market segmentation tool developed by Nielsen PRIZM to calculate the share of households in each of the four major market segments - urban, suburban, second city, and town and rural in the zip code. The segments are defined based on demographics, geographic data, and consumer behavior. If more than half of the households in the zip code belong to a specific segment, we define the zip code to be in that group. We use indicator variables (D_Urban, D_Sub, D_2ndCity, and D_Town) to denote these segment groups.[10] Our results are robust when we use an alternative threshold of 75%.

To capture the local banking market, we use the Summary of Deposits (SOD) from the FDIC to locate all bank branches in the zip code. We use the annual Retail Loan Table published by the Federal Reserve Board (from the Community Reinvestment Act) to obtain data on small business loans at the bank-county level.[11] Using banks' share of small business loans at the county level and the distribution of bank branches in the zip code, we calculate an estimate for the small-business-lending activity in the zip code. The fact that the banks are large relative to the zip substantially alleviates endogeneity issues. Since we compute banks' share at the county level, it is unlikely that opportunities in a single zip code determine our measure.

Table 1 Panel A presents the summary statistics of our sample. Brand stores are bigger and have more foot traffic. About 66% of our sample are brand stores, with the majority (94%) of them are operated by the three major national brands (CVS, Walgreens, and Rite Aid), and the rest are local or regional brands. A larger proportion of brand stores are in

[10] About 9% of our zip codes do not have a dominant market segment.

[11] https://www.federalreserve.gov/consumerscommunities/data_tables.htm. The most recent data available is from 2017.

the suburbs (28 % vs. 16% for independent stores), whereas independent stores are more likely to be in small towns (53% vs. 33%). Brand stores are in higher-income locations ($78,340 vs. $66,972), with a higher average number of banks in their zip codes.[12] Both brand stores and independent stores have a similar percentage of small business-friendly bank branches in their zip codes.

Table 1: [INSERT TABLE HERE]

3 Empirical Results

3.1 The General Effect of COVID

COVID brought a major disruption to drug stores and pharmacies. Table 2 presents the general effect of COVID on pharmacies and drug stores and the relative effects across different geographic locations and income levels. In both panels, we include county fixed effects in column 1 and control for $county \times week$ fixed effects in columns $2-3$ to account for differences in government policies that may have influenced store operations and customer behaviors. We find that foot traffic went down by 58 percent under statewide stay-at-home mandates and 34 percent after states announced to reopen for business, relative to the same month last year. In Column 2, Pharmacies in business districts are hit especially hard. Visits dropped by an additional 50 percent and 32 percent, respectively, during the stay-at-home phase and after the states reopened, compared to stores in the non-business-district zip codes in the same county and the same periods. Changes in foot traffic also vary widely by location. Urban zip codes have the biggest decline in foot traffic, followed by suburban and second-city zip codes. Rural areas are affected the least. We also find that zip codes in the top and bottom income quartile experience more declines than zip codes in the middle two quartiles.

Table 2: [INSERT TABLE HERE]

At the same time, consumers significantly decrease the radius of their shopping areas.

[12] Oberfield at al. (2020) present a model of optimal location for multi-establishment firms that is consistent with this type of locational heterogeneity between brands and independent stores.

For each week, SafeGraph reports the median distance from visitors' home census block groups to the store. To identify the home census block group for each tracked visitor, SafeGraph uses the amount of time the customer's cell phone spends in a Census block at night. The median distance from home traveled by shoppers dropped by 13 percent during the stay-at-home period. The decline more than doubled for stores in business districts, consistent with press reports that business districts lost out-of-area shoppers during the pandemic.[13] Urban and suburban zip codes also report greater than county average declines, consistent with a decrease in shopping-related commuting and leisure travel.

3.2 Brand vs. Independent Stores

While all pharmacies were hit hard by the negative COVID shock, independent stores experienced more severe outcomes. Figure 2 presents the relative differential between the brand and independent stores by week in store closure (panel A), changes in foot traffic (panel B), distance traveled (panel C), and time spent in the store (panel D). We define a store to be closed for the week if it had fewer than five visits or the decline of foot traffic is more than 90 percent compared to the same month last year. There is a spike in store closure around the end of March, as many states issued the stay-at-home mandate. The rise, however, is much steeper for independent stores. For example, the closure rate went from less than 5 percent in January to more than 15 percent in mid-April for independent stores. In comparison, the the closure rate during the same time went up from 1.4 percent to 3.5 percent for brand stores. For stores that remained open, independent stores face a greater decline in foot traffic than brand stores, with a gap of more than 20% in March and April, and then consistently at a 10% from May to October. Meanwhile, there is a change in clientele - we find that the median distance from home to store fall for both brand and independent stores, but more so for brand stores. Customers spent more time in the brand stores while less or about the same time in independent stores during the pandemic.

Figure 2: [INSERT FIGURE HERE]

The brand and independent stores are not located homogeneously, and localities may

[13]https://www.nytimes.com/2020/07/26/nyregion/nyc-coronavirus-time-life-building.html

differ in their sensitivity to the COVID shock, given demographics, business environment, and government policies. To properly draw inferences on the differential between the brand and independent stores, we need to control the store location in addition to time. Table 3 Panel A presents results on changes in foot traffic. Column 1 includes county x week fixed effects and shows that brand stores experienced a precisely estimated 7.8 percent higher year-to-year growth relative to independent stores in the same country or zip code before the pandemic. This is consistent with the shifts in the comparative advantage of chains and independent firms described by Hsieh and Rossi-Hansberg (2020) and Smith and Ocampo (2020). In columns 2, we include more granular $zip \times week$ fixed effects to control for characteristics at the zip code that may affect store traffic to pharmacies and the differential between the brand and independent stores. We include a store fixed effect in column 3 to control the brand and independent stores' pre-trend. COVID had a significant adverse effect on the market shares of independent stores. Brands have a significantly smaller foot traffic loss during the pandemic relative to independent stores in the same country or zip code. Foot traffic is 22 percentage points higher in brand stores during the stay-at-home phase, about 38 percent of the total loss. The difference becomes smaller to 10.6 percentage points (about 31 percent of the total loss) after states reopened for business.

Table 3: [INSERT TABLE HERE]

Columns 3 - 8 examine the differential between brand and independent stores by market segment. Across different locations, brand stores do relatively better in suburbs and second city zip codes and worse in urban zip codes. Brand stores also do much worse in business districts. Across income levels, brand stores do better in high-income neighborhoods but worse in low-income neighborhoods.

Examining the closure rate, we show in Table 3 Panel B that brand stores have less closure than independent stores before the pandemic. The difference more than doubled under the stay-at-home mandates and persisted after states reopened for business. Across localities, we find that closure rates are more likely for brand stores in business districts, secondary cities, town and rural areas, and low-income neighborhoods, but lower in high-income neighborhoods, urban, and suburbs.

In Table 3 Panel C, we examine the change in distance from home an average customer travels to shop to understand the reallocation of demand over the pandemic period. We find that consumers to brand stores come from more close-by areas during the pandemic than customers who shop in independent stores. The effect is more significant in urban areas, especially in business districts. One interpretation is that as offices in business districts were closed, stores there lost customers who used to visit (for work or travel) from other areas and that those customers preferred to shop in brand stores rather than independent stores.

Most of the states that issued state-level stay-at-home mandate reopened for business by the end of June. To understand the dynamics of the brand's advantage over independent stores, we re-estimate our specification in Table 3 column 3 by week. We plot the point estimator and the standard error for the coefficient for D_Brand in Figure 3. Consistent with what we estimated in Table 3, the brand-independent differential sharply shot up at the onset of the pandemic, went down in May, and has remained at a level around 10% to October.

Figure 3: [INSERT FIGURE HERE]

In summary, the increase in the market share of brand stores relative to independent stores started even before the COVID hit, consistent with the prediction of a weakening position of independents relative to brands by Hsieh and Rossi-Hansberg (2020). The COVID shock is associated with an economically significant increase in this differential. In our sample, the county-level HHI for pharmacies and drug stores increased by about 10% from March to October in 2020. The increase is more than five times faster than the annualized increase from Smith and Ocampo (2020). The increase is general but has distinctive geographical properties. It is particularly strong in high-income areas and the suburbs. The shock is also associated with a drop in the distance shoppers travel to stores, which is greater for brand stores. A significant exception is business districts, where there is more decline in foot traffic in general with more severe losses for brands than for independents. Our findings point to the fact that the effects of demand shocks in retail and services are very place-dependent, as locations are sorted by income, consumer preferences, and travel and activity patterns. Thus, an evaluation of policy responses to small business shortfalls also requires consideration of these heterogeneities.

3.3 The Paycheck Protection Program (PPP)

Congress created the Paycheck Protection Program (PPP) as part of the CARES Act passed on March 27, 2020. PPP allowed small and medium-sized firms that were substantially affected by the COVID pandemic to borrow uncollateralized, low-interest-rate loans for up to 2.5 times monthly pre-COVID payroll up to $10 million. Two tranches of PPP loans in a total of $649 billion were issued. The first tranche started on April 3, 2020, and was exhausted on April 16, 2020. The second tranche restarted from April 27, 2020, with most of the loans distributed by May 3, 2020.

We aggregate the total amount of PPP loans approved for pharmacies for each zip code by week and use the cumulative amount in the week before as our measure (PPP). It captures the total financial assistance received by pharmacies in the area, rather than specific amounts received at the store level. Our main focus is to examine how PPP loans change the differential between brands and independents. Examining the differential helps to alleviate the endogeneity concern that omitted variables may drive the approval of PPP loans and changes in store-traffic. Alternatively, it may be that PPP loans made to a zip code have a spillover effect, allowing businesses in other sectors to operate or pay their employees, thereby raising activity and foot traffic in the locality. To explore the spillovers from other industries, we calculate the total amount of PPP loans approved across all industries in the zip code (PPP_Total). We define indicators variables for receiving PPP loans for the industry (D_PPP) or across all industries (_PPP_Total). Table 4 presents our findings.

Table 4: [INSERT TABLE HERE]

We use the indicator variables for PPP loans in Panel A and the log of PPP loan amount in Panel B. For each panel, columns 1 to 3 examine the change in foot traffic, and columns 4 to 6 examine store closure. We include county-week fixed effects so we can access the general effect of PPP. To control for the size of the zip code, we control for the number of households (Ln_nhouse), the number of business establishments (Ln_estab), and the number of drug stores (Ln_nstore) in the zip code. Consistent with our discussion of demand shocks across business districts and residential areas, residential zip codes see relative increases in traffic to pharmacies. At the same time, the reverse is true for areas with more businesses.

In column 1, we find a noticeable effect from PPP - stores in zip codes that received PPP loans have 2.2 percent more foot traffic than stores in zip codes from the same county that did not receive PPP loans. The benefit of PPP loans is substantially smaller to brand stores in these zips. Since brand stores (CVS, Walgreens, and RiteAid) do not qualify for PPP loans due to their size, our results suggest that targeted PPP loans help independent drug stores catch up with their brand counterparts. In contrast, column 2 shows that the total PPP loans in the zip code do not significantly affect drug stores, nor do they lead to any differential effect between the brand and independent stores. Our result of within-industry PPP loans helping more for independent stores is robust when we include both industry PPP and total PPP loans in column 3. However, the magnitude of the effect from industry PPP loans is small (around 2.4%) - less than one-quarter of the estimated difference between the brand and independent stores after reopening (10.6%).

Columns 4 to 6 examine store closures. Zipcodes that received PPP loans have a 1.7 percent reduction in closure, compared to stores in zip codes from the same county that did not receive PPP loans. The benefit of PPP loans in preventing stores from closing is smaller for independent stores, consistent with the observation that none of the big national brand pharmacies has received PPP loans. Interestingly, we also find that the total PPP loans have a negative effect on store closure, especially for local pharmacies. Again, the magnitude of the effect from industry PPP loans, albeit statistically significant, is small economically.

Panel B presents our results using the continuous version of the PPP variables (log of the loan amount). Results are qualitatively similar. [14]

[14] For robustness check, we re-estimate the same specification using the log of the average loan amount (dividing the total loan amount by the number of total or independent drug stores in our sample) and find similar results qualitatively.

Almost all PPP loans were issued between April 3 to May 3, 2020. To analyze the effect of PPP loans over time, we further divide the post-PPP period by month and re-estimate our regression for changes of foot traffic and store closure using the specification in column 1 and column 4 from Table 4 Panel A, respectively. For each month starting from April, we estimate the main effect of PPP loans(D_PPP) and the differential effect of PPP loans for brand stores (D_PPP x D_Brand). Figure 4 presents our estimates. Immediately following PPP loans' issuance, there is a positive effect - zip codes that received PPP loans have less decline in foot traffic, and most effect accrues to independent stores. However, the effect quickly faded away and diminished by August. Our finding is consistent with the fact that the maximum amount of money a firm can borrow through the PPP is equal to 2.5 times the average payroll up to $10 million. It suggests that PPP loans only provided temporary relief to independent pharmacies to catch up with their brand counterparts. There seems to be a reversal from September after the effect of PPP ran out.

Figure 4: [INSERT FIGURE HERE]

3.4 The Role of Banking

There is considerable evidence that most small businesses borrow locally. Agarwal and Hauswald (2010) use proprietary data from a large commercial bank to estimate that the firm's median distance to the lending branch is under three miles. Nguyen (2019) finds significant adverse effects of exogenous bank branch closings on local small businesses in a radius of up to six miles around the closed branch. Using filings from the Community Reinvestment Act, Laderman (2008) finds that approximately 90 percent of small business lending is from banks with branches in the local market. These results are consistent with survey evidence from the National Federation of Independent Business Research that the median distance over which small firms search for credit is only 4.3 miles ((Amel and Brevoort (2005)). There are material differences across banks in policies on small business lending. Those policies have economically significant effects on credit and labor markets at the county level across the U.S., as shown by Chen, Hanson, and Stein (2017). The policy of the bank towards small businesses is particularly important in the current context. Using a survey of approximately 6,000 small businesses administered by Alignable, a network of small companies, Bartik et al. (2020b) show that the probability that a business obtains a PPP loan depends on the identity of its principal bank.

In our context, small-business-friendly banks may have two effects. First, and directly, they increase access to credit for independent pharmacies. This effect should help them maintain market share. Second, they may help keep a vibrant local small business ecosystem, boosting local demand. The effect of the second effect on the *relative* standing of brand and independent pharmacies is not clear. It depends on the set of firms that benefit more from access to financing - independent pharmacies or other small businesses whose employees patronize both independent and brand pharmacies. The effect may differ by the composition of small firms in the zip code, income levels, and community characteristics.

To measure the small business lending environment at the zip code level, we use the Summary of Deposits (SOD) from the FDIC to locate all bank branches in the area.[15] In our sample, an average zip code has 5.81 banks. There is a notable variable across zip codes. About 4.3 percent of the zip codes have no bank branch, and about 19 percent of the zip codes have more than ten banks. We use the annual Retail Loan Tables from the Federal Reserve Board to compute small business lending at the bank-county level. Using banks' share of small business loans at the county level and the distribution of bank branches in the zip code, we calculate an estimate for the small-business-lending activity in the zip code. The fact that the banks are large relative to the zip substantially alleviates endogeneity issues. Since we compute banks' share at the county level, it is unlikely that opportunities in a single zip code determine our measure. We define indicator variables for zip codes that are in the top quartile for small business lending activities (D_SBL). We include $zip \times week$ fixed effects in column 2 to control for omitted variables at the zip code level over time and add store fixed effects in column 3 to control for pre-trend at the store level. We find similar results. Small business lending benefits independent stores during the pandemic.

Table 5 report our findings. Column 1 shows that zip codes with more small business lending activities have a 3.4 percent higher foot traffic growth even before the COVID-pandemic. The effect is bigger during the pandemic, especially following states' reopening.

[15] https://www7.fdic.gov/sod/

Interestingly, the effect is mostly on independent stores. Small business lending has little effect on brand stores[16].

Table 5: [INSERT TABLE HERE]

4 Mechanisms

So far, we have shown that brand pharmacies experienced a smaller loss of store traffic during the COVID-pandemic. In this section, we explore potential mechanisms.

4.1 Consumer Preference

One possible explanation for the observed differential in store-traffic between the brand and independent stores is consumer preference. It is possible that as demand shifts from business districts to suburbs and from far-way to close-by stores, it affects brand stores more favorably since consumers who shop in suburbs and close-by stores prefer brands. To explore this channel, we use consumer survey data from Simmons Local Consumer Insights, a marketing database, to construct consumer preference measures. The survey measures 209 American Designated Market Areas (DMAs) using samples averaging 30,000 per market for adults age 18 and above.

First, we measure consumers' preference to shop local for each zip code based on the percentage of consumers who responded in 2019 that they prefer to shop in local stores to shopping in national chains. We define an indicator variable (D_Local) equal to one if the percentage is in the top quartile among all zip codes in our sample. Next, we construct our proxies using the percentage of respondents in the 2019 survey who said they ordered from Amazon.com in the last 30 days. We define an indicator variable (D_AMZ) equal to one if the zip code has a percentage in our sample's top quartile. Table 6 present our results.

Table 6: [INSERT TABLE HERE]

[16]The combined effect for brand stores is 3.4% - 3.1% = 0.3% before the pandemic, and is 1.4% -0.5% = 0.9% following states reopened

Panel A examines how consumer preference for local shopping affects the relative performance between brands and independents. Column 1 shows that pharmacies in areas with a strong preference for local stores have slower growth before the pandemic and experience a smaller decline during the pandemic. Moreover, when there is a strong preference for local stores, the difference between brand and independent stores shrinks. The estimated coefficient for the interaction term is 4.2% during the stay-at-home phase, and 3.3% after states reopened, about 20-30 percent of the differential between brands and independents, as documented in Table 3. Our results are robust when we include zip x week fixed effects in column 2 and with additional store fixed effects in column 3. These results suggest that differences in taste drive a significant part of the differences in store traffic between brands and independents.

In Panel B, we examine how consumers' online shopping experience affects the response between the brand and independent stores during the COVID-pandemic. We find that zip codes with more online shopping experience have a much more significant drop in store-traffic in general, both during the stay-at-home periods and after states reopened. In addition, online shopping experiences exacerbate the differential in response between the brand and independent stores. Brand stores in zip codes that fall in the top quartile in online shopping experience have an additional 2.5 to 3.7 percent higher foot traffic than other zip codes.

Thus, while online shopping growth may affect the total foot traffic in stores, it does not affect the breakdown between the brand and independent shopping in brick-and-mortar stores analyzed in this paper. However, in a broader sense, to the extent that it diverts a segment of the local retail market online, it shrinks the local market place facing independent stores. By contrast, all the brands analyzed in this paper have online ordering and delivery in addition to their brick-and-mortar stores. Moreover, online ordering brings local independents into competition with other potential sellers.

4.2 Supply Chain

Brand stores, especially large national chains such as CVS, Walgreens, and Rite-Aid, have a comprehensive distribution network. One potential advantage of brand stores is their better supply chain, which can be even helpful during a period of shortage. In this section, we test this hypothesis using the subsample of CVS stores.

We hand-collect locations of CVS's corporate distribution centers from its website. The average distance from a store to the nearest distribution center is about 76 miles, and about half of all CVS stores have a distribution center within 50 miles. Stores located closer to a distribution center may get restocked soon and thus would be less affected by an inventory shortage. We define an indicator variable (Close_to_Warehouse) that equals one if a store has at least one distribution center within 50 miles and zero otherwise. Meanwhile, if a store relies on a distribution center that also supplies to many other stores, it may be more subject to shortages as demand in other stores fluctuate. For each store, we find the closest distribution center and define an indicator variable (Busy_Warehouse) if the number of stores a distribution center has within 100 miles falls in the top quartile across all distribution centers. Using this definition, a busy distribution center in our sample has more than 1000 stores within 100 miles, compared to an average of 500 stores for a less buy distribution center. For this test, we include CVS as the other brand and exclude other brand stores that we do not have information about distribution centers.

Table 7 describes our results, in which we examine whether the proximity to a distribution center or being supplied by a busy distribution helps explain the differential between a CVS store and its local independent counterparts. In columns 1 and 2, we include zip-week fixed effects to control for demand at the zip code level. We find that brand stores have a higher differential relative to local independent stores when they are closer to a distribution center or supplied by a less busy warehouse. However, the effect is only significant initially and disappeared following the states' reopening. We include additional store fixed effects in columns 3 and 4 to control for unobserved store-level variations and find qualitatively similar results. Brand stores located closer to corporate distribution centers have a 2.8 - 4.8 percent higher differential over local independent stores, but only during the initial stage of the pandemic. Thus, our finding suggests that better access to the supply chain may have given brand stores some advantages when the pandemic first hit, but cannot explain the persistent differential we observe between the brand and independent stores in the last four months.

Table 7: [INSERT TABLE HERE]

4.3 Proximity to Medical Offices

The COVID pandemic has dramatically altered how the delivery of healthcare in the U.S. Patel et al. (2020) show that in-person medical visits dropped by 30 percent from January to June 2020, replaced by telemedicine visits. The drop in on-site medical visits undoubtedly would have affected foot traffic for nearby pharmacies and drug stores. If independent pharmacies are more likely to co-locate with medical practices, then they would have been more severely affected by the decline in in-office visits.

To investigate this hypothesis, we identify medical offices or facilities within 100 or 200 yards from the drug stores and pharmacies in our sample [17]. Independent stores are indeed more likely to co-locate with medical offices - 8.8 percent and 20 percent of independent stores in our sample have at least one medical office within 100 or 200 yards, respectively. In comparison, 3.6 percent of brand stores have at least one medical office within 100 yards, and 13 percent within 200 yards. In Table 8, we examine whether the proximity to medical offices and facilities helps explain the brand-independent differential. Panel A uses a radius of 100 yards, and Panel B uses a radius of 200 yards. Column 1 shows that, not surprisingly, stores next to medical offices experienced 11 percent more loss in foot traffic, but only in the early stage of the pandemic. Conditional on being next to a medical office, the effect is homogeneous across the brand and independent stores. We include additional store fixed effects in column 2 and find similar results. In column 3, we exclude all stores within 100 yards of any medical office and re-estimate our main specification. The estimated coefficient for brand-independent differential remains almost changed from our estimate using the entire sample (0.222 to 0.214). Our results are robust when we locate medical offices within 200 yards of drug stores or pharmacies.

Overall, our finding suggests that the differential between the brand and independent stores we documented is unlikely to be driven by the negative spillover from declines in on-site medical visits.

[17] We use the following 3-digit NAICS to identify medical offices: 621, 622, and 623

Table 8: [INSERT TABLE HERE]

4.4 Testing Centers and In-Store Clinics

Many brand pharmacies have set up testing centers to offer COVID testing. In addition, brand stores such as CVS offer on-site medical clinics that may be in high-demand during the pandemic. Can testing centers and on-site clinics explain the brand-independent differential that has been quite persistent since June? In this section, we explicitly consider the stores that offer COVID testing or have on-site clinics.

For the largest brand pharmacy in our sample, CVS, we hand-collect locations that offer COVID testing over time. CVS first started to offer COVID testing in mid-May in about 300 stores. By early October, more than 3000 stores in our sample participate in COVID testing. We define an indicator variable (D_Testing) that equals one if a CVS store offers COVID testing during that week and zero otherwise. For this test, we only brand stores from CVS and exclude other brands.

Table 9 Panel A reports our results. D_Brand equals one for all CVS stores, and D_Brand x D_Testing is the marginal effect of CVS stores that participate in COVID testing. Column 1 includes zip x week fixed effects, and column 2 includes additional store fixed effects. We find that on-site COVID testing increase store traffic by $4 - 6.4$ percent during the week. However, explicitly considering testing centers does not change the estimated differential between the brand and independent stores. In column 3, we exclude all active testing centers and re-estimate our main specification. We find no significant change in our estimates for the brand differential. Overall, our results show that on-site testing initiation does increase foot traffic beyond the pure brand effect at a store significantly, but controlling for testing sites does not change our results.

Table 9: [INSERT TABLE HERE]

For the same CVS sample, we hand-collect locations that offer on-site clinics ("Minute-Clinic") in January 2020 before the pandemic hit. On-site clinics offer convenient walk-in visits for routine family care, including minor illness, injuries, screening, vaccinations, and related services. About 12 percent of all CVS stores in our sample have an on-site clinic, and those stores tend to have more space and locate in suburbs and high-income neighborhoods. We define an indicator variable (D_MC) that equals one if a CVS store offers an on-site clinic and zero otherwise. We only include brand stores from CVS for this test. Thus, variable D_Brand captures the differential between a CVS store and its local independent counterparts, and the interaction term, D_Brand x D_MC, captures the marginal effect of having an on-site clinic. Unlike the testing cites, which appeared from the end of May, on-site clinics exist during our entire sample. We define a triple-interaction term between D_Brand x D_MC and our time indicator, SAH, to examine the effect of on-site clinic before and during the pandemic's first and second stages. Table 9 Panel B reports our results. Column 1 includes zip x week fixed effects, and column 2 includes additional store fixed effects. We find that on-site clinics have a negative effect during the initial stage of the pandemic but a positive effect in later stages. In both cases, the magnitude is small and less than 2 percent. Since on-site clinic tend to be in larger stores, in columns 3 and 4, we include additional controls for store size. We define an indicator variable, D_Large, that equals one if a store is in the top quartile by size. Our results are robust.

4.5 The Competitive Channel

For our sample, the advantages of brands stores posited in Oberfield et al. (2020) would cause the brands, which are more productive and rely on technology and more bureaucratic processes, to build larger establishments in more affluent, customer-dense locations, trading off the additional fixed locational costs, such as higher rent, against the benefits of customer access, which they can exploit better than the independent stores. Consistent with this, we predict that brands will select locations that tend to be richer, in more heavily trafficked areas, and build stores that are larger and have higher volumes in the pre-COVID status quo. These locations are not optimized for the COVID shock and may do relatively better or worse than the locations where the direct shock. However, if the initial locational choices reflect brands' comparative advantage in attracting customers, we expect that brands' performance post-shock will be better than the performance of independents in those locations. Below we test these conjectures.

If they are more productive, the brands will locate in higher-income areas, build larger stores, and in areas that are more customer dense. Sample statistics in Table 1 show that indeed brand stores are larger and located in higher-income areas. Accordingly, we next examine whether brand stores are located in more customer-dense areas. In most of our tests, we have already included zip x week fixed effects, which help control local characteristics such as demographics, business establishments, and government policies. Nevertheless, within a zip code, locations may still differ in terms of sensitivity to demand shocks. Here, we zoom in to more granular locations immediately around the drug stores and pharmacies in our sample and test whether the brand-independent store differential can be explained by micro-areas in which they are located. For each store in our sample, we locate all establishments within a 200 or 500 yard and calculate the average foot traffic in January (before COVID), together with foot traffic changes over time. Table 10 Panel A shows that stores next to a brand store have higher foot traffic than stores next to an independent store before the pandemic hit. Our finding is consistent with Oberfield et al. (2020), who suggests that brand stores are located in more customer-dense locations.

Table 10: [INSERT TABLE HERE]

In Panel B, we compare foot traffic changes for stores near a brand store and stores near a local store. Just as the brand store itself, stores near a brand pharmacy also experience less foot traffic decline than stores near an independent pharmacy during the pandemic. Interestingly, column (3) shows that brand drug stores perform comparatively better, relative to nearby stores, than independent pharmacies.

We can estimate how the differential between stores near the brand or independent pharmacies by week. We follow the same specification used in Section 3.1, using a weekly time indicator instead of the three-period stay-at-home indicator. Figure 5 plots the estimated coefficient for the brand-independent differential by week. We observe a similar pattern as that in Figure 3 (when we estimate the brand effect for the drug store themselves). There is a sharp increase in the differential between near-brand and near-independent stores in March, which later stabilized at a lower level. Our results are robust when we only look at business-related establishments in the nearby area (NAICS code from 40 to 89) or using weighted average changes based on initial traffic.

Figure 5: [INSERT FIGURE HERE]

We show in Table 10 that stores near brand pharmacies have higher foot traffic before the pandemic hit and that these difference persist throughout the sample period. These findings, together with the earlier findings on income and store size are consistent with the conjecture that brand stores are are more productive. However, since brand pharmacies perform comparatively better than nearby stores during the pandemic (Panel B of Table 10) we cannot conclude that their outcomes following the shock are entirely driven by their location in more heavily trafficked areas.

To directly test the prediction in Oberfield et al. (2020) related to size, productivity, and location choices, we examine how outcomes depend on initial pharmacy foot traffic and store size. We define large pharmacies as stores in the top quartile in size or the initial number of visits in January 2020 (D_Large). An average large pharmacy in our sample occupies about 20,000 square feet, more than twice as big as the average store. 28 percent of brand stores and 20 percent of independent stores in our sample belong to the large group.

Columns 1 and 2 of Table 11 show that controlling for zip-week fixed effects, highly trafficked pharmacies suffer a sharper drop in traffic when the shock hits. During the entire period, the most highly trafficked pharmacies in each zip code suffer the greatest declines in foot traffic.[18]. However, brand pharmacies, as predicted by their comparative advantage, nullify this initial disadvantage following the exogenous COVID shock.

Table 11, columns 3 and 4, show a similar pattern for firm size. Large stores had a lower growth before the pandemic and experienced bigger store traffic declines during the pandemic. The pattern is reversed for brand pharmacies – large brand stores do better than other brand stores.

These results are consistent with the hypothesis that national brand stores favor larger, more customer dense locations in higher-income zip codes. These locations were partic-

[18]This is consistent with those pharmacies being located so as to optimally exploit pre-COVID traffic patterns and not being so located following the shock.

ularly badly affected by the unexpected exogenous COVID shock. However, brands were particularly able to gain relative to independents in large and initially highly trafficked brand stores. Thus, the observed outcomes is consistent with the product market comparative advantage of brands.

Table 11: [INSERT TABLE HERE]

5 Conclusion

The COVID pandemic transformed retail markets across the U.S. The demand shock arrived in markets at a time when small independent stores were under growing competitive pressure from large national chains. Using granular real-time measures of foot traffic and closures at the establishment level in pharmacies, we show that the demand shock reduced foot-traffic and increased closures across the board, but that the reductions were uneven, affecting some locations such as business districts and high-income areas more than rural areas. The COVID shock was accompanied by a specific form of demand reallocation of store traffic. Shoppers became more local, living in closer vicinity to the stores. We show that this created a split between residential localities that gained demand (relatively) and business areas that lost demand. The composition of customers changed for all pharmacies, with shoppers now shopping closer to they live. This effect is most evident in particular for brand pharmacies.

As demand was reallocated, the national chains gained customers relative independent stores in most locations. Since the preservation and growth of small businesses is a U.S. government policy objective, the Federal government instituted measures to subsidize small businesses during the initial phases of the pandemic. Our granular data enables us to track to observe the effect of government-subsidized loans to small businesses and local banking markets across different localities and across time. We find that subsidized loans through the PPP program had a measurable effect on the competitive response of independent stores that received those loans. These stores initially made up about a quarter or so of the loss of foot-traffic relative to brand stores, but the effect was transient.

We also find that the composition of the local banking market is significantly associated with a stronger competitive response of independent stores. Banks differ by the extent to which they are small-firm friendly in making loans to small businesses. We find that the presence of branches of small-firm-friendly banks close-by is associated with a stronger competitive response by independent stores. This effect occurs early in the pandemic before the application process for PPP loans was opened up. Thus, small-firm-friendly banks are also associated with a competitive response by independent stores that makes up a quarter or so of the loss of foot traffic in the early days of the pandemic. These results point to the importance of local bank markets in mitigating real demand shocks and preserving small businesses.

The broad shift to national chains over the whole sample period cannot be explained by disruptions to supply chains, declines in outpatient doctor visits or COVID testing in specific pharmacies. The relative gains by brands are better explained by their ability to exploit the reallocation of demand as consumers responded to the pandemic. Models of productive multi-establishment service predict that firms invest in large establishments in customer-dense areas when they face high fixed costs and low marginal costs, giving them an advantage in acquiring new customers at the margin once costs of store location are sunk. We show that prior to the pandemic, brands invested in larger stores in customer-dense locations. The pandemic acted as a natural experiment. Although it turned out that large stores and customer-dense locations suffered greater declines in demand, in these locations brand stores gained the most relative to independent stores. The brands' superior performance also persists at the granular level when we control for initial nearby foot-traffic for stores in a radius of 200 or 500 yards around each drug store in our sample. This pattern of outcomes is consistent with the hypothesis that the gains of brand stores are due to their costs structures and that they are more productive than independent stores in general.

Amid falling business entry rates, small retail and service businesses have been a bright hope in reallocating entrepreneurship from manufacturing industries. We show that in small businesses the retail pharmacy sector are competing with formidable competition from chains which are more productive at the current state of technology. If the reallocation we observe in retail pharmacies in response to COVID is general across other retail and face-to-face service activities, we can expect a reduction in the opportunities for traditional small businesses. Our results indicate that the presence of small-business-friendly banks may be a factor in how this plays out across localities but will likely not affect the final outcomes.

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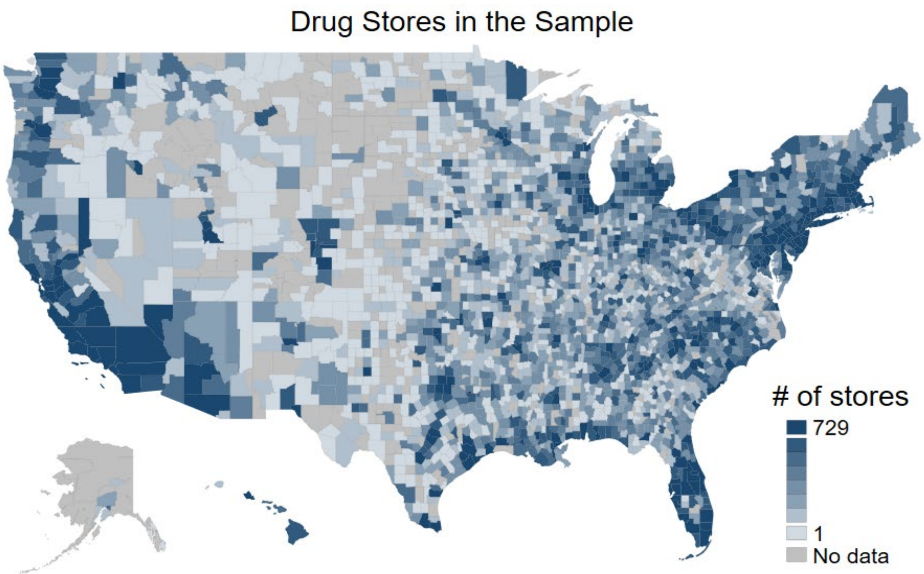
Figure 1: Sample Distribution

Panel A presents the distribution of stores at the county level in our sample and Panel B presents the percentage of brand stores by county.

Panel A: Stores by County



Panel B: Percentage of Brand Stores by County

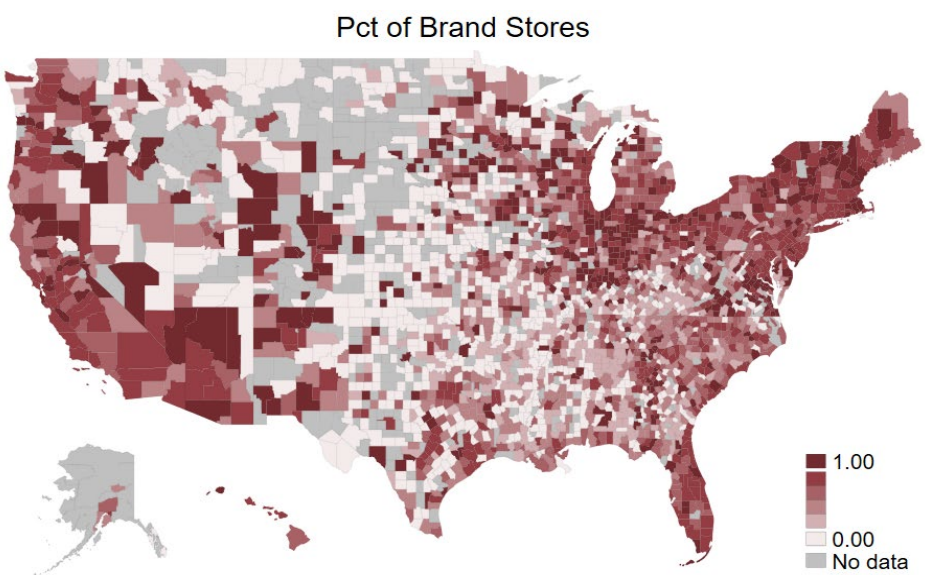


Figure 2: Brand vs. Independent Stores - Summary Statistics

This figure shows the percentage of stores closed (Panel A), the average change in the number of visits (Panel B), the average change in distance traveled (Panel C), and the average change in time spent in the store (Panel D) over our sample period for brand stores and independent stores.

Panel A

Panel B

Figure 3: The Estimated Brand-Independent Gap by Week

The figures here present the point estimator and the standard error for the brand indicators over time (β_t's) by week. We use the following specification:

$$\Delta y_{izt} = \beta_0 + \sum_{\tau} \beta_\tau \times Brand_i \times 1_{t=\tau} + f_i + \alpha_{zt}$$

where y_izt is foot traffic for store i in location z during week t.

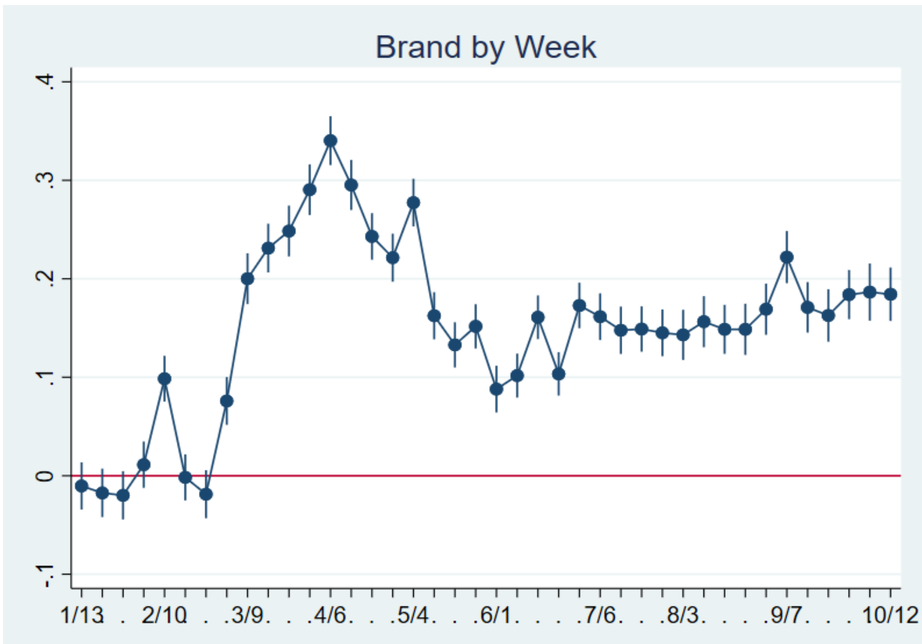


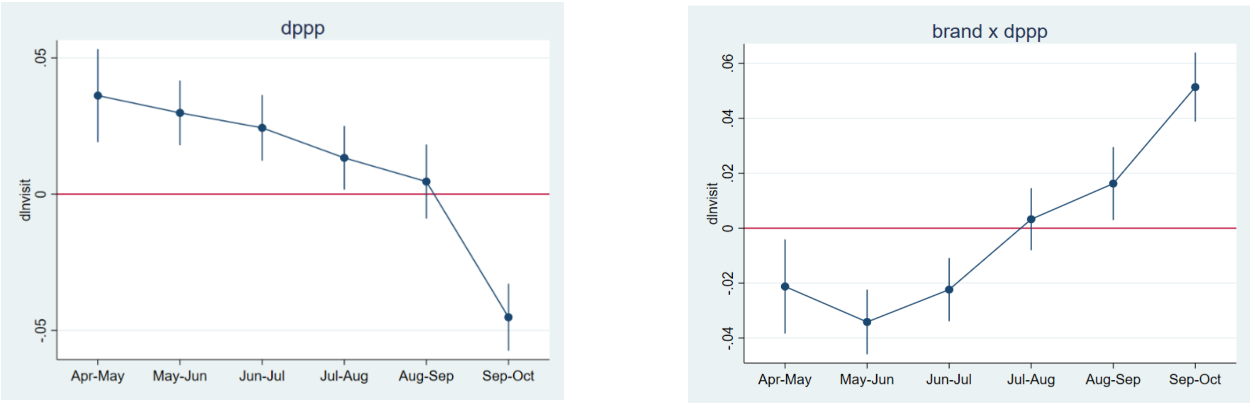
Figure 4: The Effect of PPP Loans Over Time

The figures here present the point estimator and the standard error for the PPP indicator (dppp) and the interaction of the PPP indicator and the brand indicator (brand x dppp). We use the following specification:

$$y_{izt} = \beta_0 + \sum_{\tau} \beta_\tau \times Brand_i \times 1_{t=\tau} + \sum_{\tau} \gamma_\tau \times PPP_{z\tau} \times 1_{t=\tau} + \sum_{\tau} \delta_\tau \times Brand_i \times PPP_{z\tau} \times 1_{t=\tau} + f_i + \phi X_z + \alpha_{ct}$$

for store i in zip code z during week t, including county x week fixed effects (for store i in zip code z during week t, including county x week fixed effects (α_ct), zip level control variables (X_z) and store fixed effects(f_i). The dependent variable in Panel A is the change in foot traffic, and the dependent variable in Panel B is an indicator variable for store closing. In each regression, we include a monthly dummy

Panel A: Change in # of Visits



Panel B: Store Closing

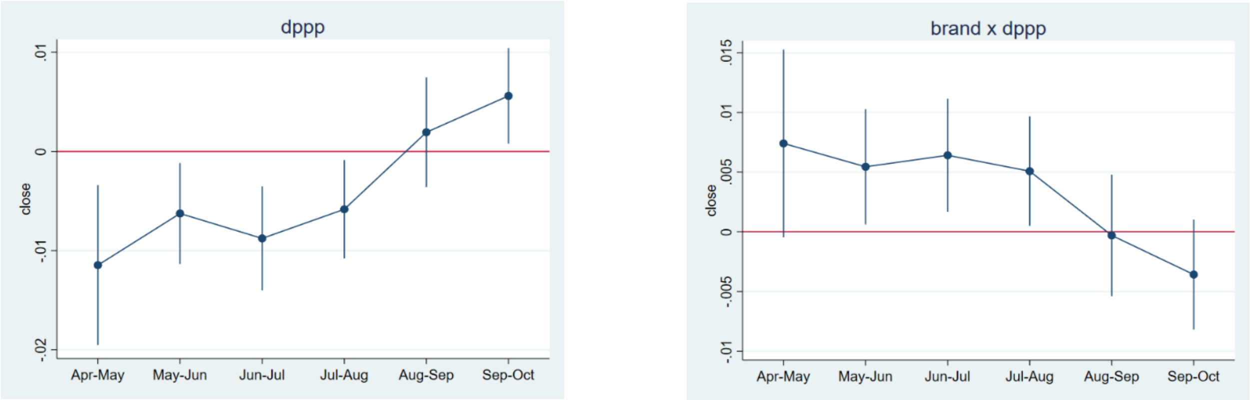


Figure 5: The Estimated Brand-Independent Gap for Nearby Stores

The figures here present the point estimator and the standard error for the brand indicators over time (β_t's) by week for stores within a 200-yd radius of drug stores and pharmacies in our sample. We use the following specification:

$$\Delta y_{izt} = \beta_0 + \sum_{\tau} \beta_\tau \times Brand_i \times 1_{t=\tau} + f_i + \alpha_{zt}$$

where y_izt is the average foot traffic for stores near drug store i in location z during week t.

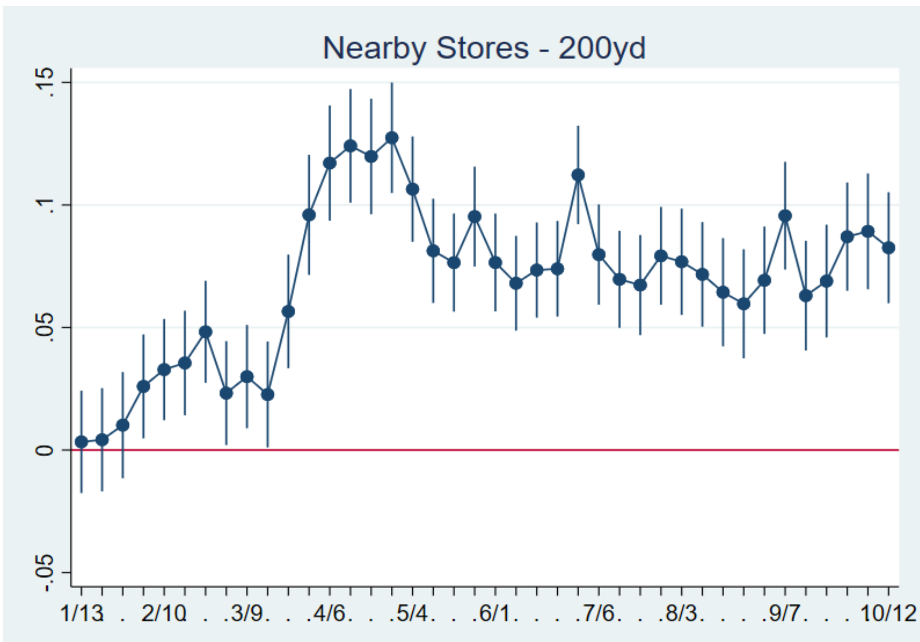


Table 1: Summary Statistitics

This table reports the summary statistics of stores used in our sample. In Panel A, we report summary statistics for two subgroups - independent stores (column 1) and brand stores (column 2), and the entire sample. D_Brand is an indicator variable that equals one if the store belongs to a brand identified by SafeGraph. % of Urban, % of Suburb, % of 2ndCity, and % of Town and Rural are percentages of households in the zip code that classified as Urban, Suburban, Second City, and Town and Rural by the PRIZM Premier database. D_BDistrict is an indicator variable that equals one if the ratio of business employment over the residential population in the zip code is greater than two and zero otherwise. D_LowInc and D_HighInc are indicator variables that equal one for the bottom and top quartile of income levels, respectively. # of Banks is the number of bank branches in the zip code, and Exp_SBL is the estimated measure of exposure to small business lending as described in the Data Section. Panel B reports the distribution of our sample across states.

Panel A

	Independent Stores	**Brand Stores**	**Total**
Square Feet	9,150	13,287	11,892
# of Visits (Jan 2020)	231.442	515.494	419.731
% of Urban	0.174	0.187	0.183
% of Suburb	0.159	0.281	0.24
% of 2ndCity	0.142	0.202	0.182
% of Town & Rural	0.526	0.33	0.396
D_BDistrict	0.016	0.020	0.019
D_LowInc	0.313	0.175	0.221
D_HighInc	0.225	0.393	0.337
Median Household Income	66,972	78,340	74,507
# of Banks	7.08	8.58	8.08
Exp_SBL	0.75	0.83	0.80
# of Obs	9,379	18,441	27,820

Panel B

State	Frequency	Percent	State	Frequency	Percent
AK	18	0.10	MS	331	1.20
AL	556	2.00	MT	79	0.30
AR	355	1.30	NC	1,041	3.70
AZ	410	1.50	ND	51	0.20
CA	2,678	9.60	NE	182	0.70
CO	227	0.80	NH	140	0.50
CT	345	1.20	NJ	955	3.40
DC	77	0.30	NM	124	0.40
DE	126	0.50	NV	195	0.70
FL	1,975	7.10	NY	2,070	7.40
GA	932	3.40	OH	1,057	3.80
HI	72	0.30	OK	379	1.40
IA	280	1.00	OR	213	0.80
ID	86	0.30	PA	1,465	5.30
IL	996	3.60	RI	103	0.40
IN	584	2.10	SC	508	1.80
KS	284	1.00	SD	80	0.30
KY	491	1.80	TN	591	2.10
LA	571	2.10	TX	2,045	7.40
MA	623	2.20	UT	130	0.50
MD	450	1.60	VA	640	2.30
ME	130	0.50	VT	72	0.30
MI	1,103	4.00	WA	437	1.60
MN	349	1.30	WI	426	1.50
MO	558	2.00	WV	204	0.70
			WY	26	0.10
Total				**27,820**	**100.00**

Table 2: Changes in Foot Traffic by Zipcode Characteristics

This table reports regression results to examine the general effect of COVID using a weekly panel.The dependent variable is the change in the number of visits (Panel A) or median distance of visitors (Panel B) from the same month last year. SAH is an indicator variable that equals one if the state has issued a stay-at-home order during the week, two if the state has reopened for businesses following the stay-at-home order, and zero otherwise. D_BDistrict is an indicator variable that equals one if the business-residential ratio is above two, and zero otherwise, D_Urban, D_Suburb, D_2ndCity, and D_Town are indicator variables that equal one if the percentage of urban, suburban, second city, and town and rural households is greater than 50%, respectively. D_LowInc and D_HighInc are indicator variables that equal one for the bottom and top quartile of income levels, respectively. Fixed effects included in each regression are indicated in the column. Standard errors clustered by county x week are reporeted in parentheses. *, **, *** represent significance at 10%, 5%, and 1%, respectively.

	Panel A DEP VAR = Change in the # of Visits					Panel B DEP VAR = Change in Distance Traveled				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
SAH =1	-0.583***					-0.127***				
	(0.010)					(0.005)				
SAH =2	-0.344***					0.005**				
	(0.011)					(0.002)				
(SAH = 1) x D_BDistrict		-0.497***			-0.490***		-0.131***			-0.129***
		(0.051)			(0.018)		(0.030)			(0.021)
(SAH = 2) x D_BDistrict		-0.322***			-0.322***		-0.028			-0.028*
		(0.049)			(0.014)		(0.041)			(0.016)
(SAH = 1) x D_Urban			-0.138***		-0.127***				-0.010	-0.004
			(0.008)		(0.007)				(0.010)	(0.006)
(SAH = 2) x D_Urban			-0.118***		-0.101***				0.011	0.011***
			(0.006)		(0.006)				(0.008)	(0.004)
(SAH = 1) x D_Suburb			-0.076***		-0.066***				0.003	-0.001
			(0.005)		(0.005)				(0.009)	(0.005)
(SAH = 2) x D_Suburb			-0.020***		-0.017***				-0.008	-0.007**
			(0.004)		(0.004)				(0.006)	(0.003)
(SAH = 1) x D_2ndCity			-0.046***		-0.056***			-0.055***		-0.050***
			(0.006)		(0.007)			(0.008)		(0.008)
(SAH = 2) x D_2ndCity			-0.050***		-0.042***			0.005		0.001
			(0.004)		(0.004)			(0.005)		(0.006)
(SAH = 1) x D_Town			-0.005		-0.001			-0.013**		-0.012**
			(0.005)		(0.005)			(0.006)		(0.006)
(SAH = 2) x D_Town			-0.003		-0.003			-0.004		-0.002
			(0.004)		(0.004)			(0.004)		(0.004)
(SAH = 1) x D_LowInc				-0.015	0.004			-0.008		-0.007
				(0.014)	(0.005)			(0.007)		(0.007)
(SAH = 2) x D_LowInc				-0.041***	-0.023***			0.005		-0.002
				(0.010)	(0.004)			(0.004)		(0.005)
(SAH = 1) x D_HighInc				-0.024	-0.028***			0.001		0.000
				(0.015)	(0.005)			(0.006)		(0.006)
(SAH = 2) x D_HighInc				0.007	-0.006*			-0.005		-0.003
				(0.009)	(0.003)			(0.004)		(0.004)
Constant	0.112***	-0.154***	-0.132***	-0.153***	-0.126***	-0.063***	-0.076***	-0.074***	-0.076***	-0.073***
	(0.007)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)	(0.002)	(0.002)	(0.002)
Observations	1,065,673	1,040,948	1,039,933	1,040,948	1,039,933	997,452	972,271	971,481	972,271	971,481
Store FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	No	No	No	No	Yes	No	No	No	No
County-Week FE	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Adjusted R-squared	0.459	0.514	0.513	0.512	0.515	0.183	0.231	0.231	0.231	0.231

Table 3: Brand Stores vs. Independent Stores

This table reports regression results to examine the differential between brand and independent stores using a weekly panel. The dependent variable is the change in the number of visits (Panel A), the rate of store closing (Panel B), or the change in distance traveled by customers (Panel C). D_Brand is an indicator variable that equals one if the store belongs to a brand, and zero otherwise. SAH is an indicator variable that equals one if the state has issued a stay-at-home order during the week, two if the state has reopened for businesses following the stay-at-home order, and zero otherwise. D_BDistrict is an indicator variable that equals one if the business-residential ratio is above two, and zero otherwise, D_Urban, D_Suburb, D_2ndCity, and D_Town are indicator variables that equal one if the percentage of urban, suburban, second city, and town and rural households is greater than 50%, respectively. D_LowInc and D_HighInc are indicator variables that equal one for the bottom and top quartile of income levels, respectively. Fixed effects included in each regression are indicated in the column. Standard errors clustered by county x week are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1%, respectively.

Panel A

DEP VAR = Change in the # of Visits	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D_Brand	0.078***	0.078***						
	(0.003)	(0.003)						
(SAH=1) x D_Brand	0.209***	0.223***	0.222***	0.227***	0.234***	0.217***	0.226***	0.236***
	(0.007)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.012)	(0.013)
(SAH=2) x D_Brand	0.101***	0.097***	0.106***	0.109***	0.111***	0.104***	0.111***	0.114***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.009)	(0.009)
(SAH=1) x D_Brand x D_BDistrict				-0.258***				-0.233***
				(0.037)				(0.038)
(SAH=2) x D_Brand x D_BDistrict				-0.172***				-0.145***
				(0.029)				(0.029)
(SAH=1) x D_Brand x D_LowInc					-0.050***			-0.045***
					(0.010)			(0.011)
(SAH=2) x D_Brand x D_LowInc					-0.018***			-0.015*
					(0.007)			(0.008)
(SAH=1) x D_Brand x D_HighInc						0.018*		-0.015
						(0.010)		(0.012)
(SAH=2) x D_Brand x D_HighInc						0.008		-0.005
						(0.007)		(0.009)
(SAH=1) x D_Brand x D_Urban							-0.038**	-0.020
							(0.016)	(0.017)
(SAH=2) x D_Brand x D_Urban							-0.055***	-0.046***
							(0.013)	(0.013)
(SAH=1) x D_Brand x D_Suburb							0.045***	0.052***
							(0.016)	(0.018)
(SAH=2) x D_Brand x D_Suburb							0.029**	0.032**
							(0.012)	(0.013)
(SAH=1) x D_Brand x D_2ndCity							0.019	0.033*
							(0.017)	(0.018)
(SAH=2) x D_Brand x D_2ndCity							0.034***	0.039***
							(0.012)	(0.012)
(SAH=1) x D_Brand x D_Town							-0.021	-0.015
							(0.014)	(0.014)
(SAH=2) x D_Brand x D_Town							-0.006	-0.004
							(0.010)	(0.010)
Constant	-0.270***	-0.283***	-0.232***	-0.232***	-0.233***	-0.233***	-0.234***	-0.234***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	1,040,948	876,506	876,506	876,506	876,506	876,506	876,173	876,173
Store FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
County-Week FE	Yes	No	No	No	No	No	No	No
ZIP-Week FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.264	0.301	0.519	0.519	0.519	0.519	0.520	0.520

Panel B

DEP VAR = Store Closing	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D_Brand	-0.052***	-0.051***						
	(0.001)	(0.001)						
(SAH=1) x D_Brand	-0.076***	-0.083***	-0.080***	-0.082***	-0.088***	-0.073***	-0.075***	-0.078***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.005)	(0.006)
(SAH=2) x D_Brand	-0.031***	-0.031***	-0.026***	-0.026***	-0.026***	-0.027***	-0.025***	-0.027***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)	(0.003)
(SAH=1) x D_Brand x D_BDistrict				0.102***				0.107***
				(0.020)				(0.021)
(SAH=2) x D_Brand x D_BDistrict				0.021*				0.020*
				(0.012)				(0.012)
(SAH=1) x D_Brand x D_LowInc					0.031***			0.022***
					(0.004)			(0.005)
(SAH=2) x D_Brand x D_LowInc					0.001			0.000
					(0.003)			(0.003)
(SAH=1) x D_Brand x D_HighInc						-0.023***		-0.001
						(0.005)		(0.006)
(SAH=2) x D_Brand x D_HighInc						0.002		0.010***
						(0.003)		(0.004)
(SAH=1) x D_Brand x D_Urban							-0.019***	-0.027***
							(0.007)	(0.007)
(SAH=2) x D_Brand x D_Urban							-0.011**	-0.012***
							(0.004)	(0.004)
(SAH=1) x D_Brand x D_Suburb							-0.033***	-0.031***
							(0.007)	(0.008)
(SAH=2) x D_Brand x D_Suburb							-0.010**	-0.016***
							(0.004)	(0.005)
(SAH=1) x D_Brand x D_2ndCity							0.021***	0.012
							(0.007)	(0.007)
(SAH=2) x D_Brand x D_2ndCity							0.001	0.003
							(0.004)	(0.004)
(SAH=1) x D_Brand x D_Town							0.012*	0.009
							(0.006)	(0.006)
(SAH=2) x D_Brand x D_Town							0.009**	0.010***
							(0.004)	(0.004)
Constant	0.102***	0.103***	0.066***	0.066***	0.066***	0.066***	0.067***	0.066***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	1,055,519	891,221	891,221	891,221	891,221	891,221	890,878	890,878
Store FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
County-Week	Yes	No	No	No	No	No	No	No
ZIP-Week FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.0578	0.0608	0.378	0.378	0.378	0.378	0.378	0.378

Panel C

DEP VAR = Change in Distance	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D_Brand	-0.032***	-0.042***						
	(0.002)	(0.003)						
(SAH=1) x D_Brand	-0.038***	-0.050***	-0.052***	-0.050***	-0.049***	-0.045***	-0.056***	-0.044***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.014)	(0.014)
(SAH=2) x D_Brand	-0.048***	-0.046***	-0.049***	-0.048***	-0.047***	-0.044***	-0.026***	-0.022**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.009)	(0.009)
(SAH=1) x D_Brand x D_BDistrict				-0.127**				0.003
				(0.051)				(0.019)
(SAH=2) x D_Brand x D_BDistrict				-0.064**				-0.078***
				(0.033)				(0.012)
(SAH=1) x D_Brand x D_LowInc					-0.013			0.009
					(0.012)			(0.019)
(SAH=2) x D_Brand x D_LowInc					-0.006			-0.021
					(0.007)			(0.013)
(SAH=1) x D_Brand x D_HighInc						-0.024**		-0.013
						(0.011)		(0.020)
(SAH=2) x D_Brand x D_HighInc						-0.015**		-0.017
						(0.007)		(0.013)
(SAH=1) x D_Brand x D_Urban							-0.005	0.023
							(0.019)	(0.016)
(SAH=2) x D_Brand x D_Urban							-0.081***	0.012
							(0.012)	(0.011)
(SAH=1) x D_Brand x D_Suburb							-0.008	-0.108**
							(0.018)	(0.052)
(SAH=2) x D_Brand x D_Suburb							-0.029**	-0.027
							(0.012)	(0.033)
(SAH=1) x D_Brand x D_2ndCity							-0.015	-0.024*
							(0.019)	(0.013)
(SAH=2) x D_Brand x D_2ndCity							-0.017	-0.008
							(0.012)	(0.008)
(SAH=1) x D_Brand x D_Town							0.020	-0.034**
							(0.016)	(0.014)
(SAH=2) x D_Brand x D_Town							0.010	-0.015
							(0.010)	(0.009)
Constant	-0.032***	-0.016***	-0.045***	-0.045***	-0.046***	-0.044***	-0.044***	-0.044***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	972,360	809,454	809,356	809,356	809,356	809,356	809,116	809,116
Store FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
County-Week	Yes	No	No	No	No	No	No	No
ZIP-Week FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.0724	0.106	0.236	0.236	0.236	0.236	0.236	0.236

Table 4: The Impact of PPP Loans

This table reports regression results to examine the impact of PPP loans between the brand and independent stores using a weekly panel. The dependent variable is the change in the number of visits from the same month last year (Panel A) or an indicator for store closing (Panel B). We define store closing as an indicator equal to one if fewer than 5 visits occurred during the week or the decline in the number of visits is more than 90%. D_Brand is an indicator variable that equals one if the store belongs to a brand and zero otherwise. SAH is an indicator variable that equals one if the state has issued a stay-at-home order during the week, two if the state has reopened for businesses following the stay-at-home order, and zero otherwise. PPP and PPP_Total measure the industry-level or total PPP loans approved by the beginning of the week for the zip code. We use an indicator variable for PPP and PPP_Total for Panel A, and the log of the PPP loan amount divided by 10 for Panel B. Ln_estab, Ln_household, and Ln_nstore is the log of the number of business establishments, the log of the number of households, and log of the number of pharmacies in the zip code, respectively. Fixed effects included in each regression are indicated in the column. Standard errors clustered by county x week are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1%, respectively.

Panel A: PPP Indicators

	DEP VAR: Change in # of Visits			DEP VAR: Store Closing		
	(1)	(2)	(3)	(4)	(5)	(6)
D_Brand	0.081***	0.078***	0.079***	-0.051***	-0.051***	-0.051***
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
(SAH=1) x D_Brand	0.220***	0.207***	0.205***	-0.080***	-0.088***	-0.086***
	(0.006)	(0.009)	(0.009)	(0.003)	(0.003)	(0.003)
(SAH=2) x D_Brand	0.106***	0.087***	0.089***	-0.039***	-0.045***	-0.046***
	(0.004)	(0.008)	(0.008)	(0.002)	(0.003)	(0.003)
PPP	0.022***		0.024***	-0.017***		-0.016***
	(0.004)		(0.004)	(0.002)		(0.002)
D_Brand x PPP	-0.011***		-0.014***	0.013***		0.012***
	(0.004)		(0.004)	(0.001)		(0.002)
PPP_total		0.006	0.001		-0.019***	-0.015***
		(0.012)	(0.012)		(0.006)	(0.006)
D_Brand x PPP_total		0.013	0.021**		0.015***	0.009***
		(0.008)	(0.009)		(0.003)	(0.003)
Ln_estab	-0.051***	-0.051***	-0.051***	0.002**	0.002**	0.002**
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
(SAH=1) x Ln_estab	-0.220***	-0.219***	-0.220***	0.049***	0.049***	0.050***
	(0.006)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)
(SAH=2) x Ln_estab	-0.110***	-0.109***	-0.110***	0.015***	0.014***	0.015***
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Ln_household	0.044***	0.044***	0.044***	-0.015***	-0.015***	-0.015***
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
(SAH =1) x Ln_household	0.192***	0.192***	0.192***	-0.064***	-0.063***	-0.063***
	(0.007)	(0.007)	(0.007)	(0.004)	(0.004)	(0.004)
(SAH =2) x Ln_household	0.112***	0.112***	0.112***	-0.027***	-0.027***	-0.027***
	(0.004)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)
Ln_nstore	-0.001	-0.001	-0.001	0.011***	0.011***	0.011***
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
(SAH =1) x Ln_nstore	0.006	0.008	0.007	0.010***	0.009***	0.010***
	(0.005)	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)
(SAH =2) x Ln_nstore	-0.012***	-0.010***	-0.012***	0.009***	0.008***	0.009***
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Constant	-0.524***	-0.527***	-0.524***	0.254***	0.265***	0.263***
	(0.012)	(0.015)	(0.015)	(0.005)	(0.006)	(0.006)
Observations	1,040,948	1,040,948	1,040,948	1,055,519	1,055,519	1,055,519
Store FE	No	No	No	No	No	No
County-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.274	0.274	0.274	0.0622	0.0620	0.0622

Panel B: PPP Loan Amount

	DEP VAR: Change in # of Visits			DEP VAR: Store Closing		
	(1)	(2)	(3)	(4)	(5)	(6)
D_Brand	0.081***	0.080***	0.080***	-0.051***	-0.051***	-0.052***
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
(SAH=1) x D_Brand	0.220***	0.219***	0.216***	-0.080***	-0.089***	-0.086***
	(0.006)	(0.009)	(0.009)	(0.003)	(0.003)	(0.003)
(SAH=2) x D_Brand	0.108***	0.102***	0.103***	-0.040***	-0.046***	-0.046***
	(0.004)	(0.008)	(0.008)	(0.002)	(0.003)	(0.003)
PPP	0.021***		0.021***	-0.015***		-0.014***
	(0.003)		(0.003)	(0.001)		(0.001)
D_Brand x PPP	-0.010***		-0.011***	0.011***		0.010***
	(0.003)		(0.003)	(0.001)		(0.001)
PPP_total		-0.017**	-0.021***		-0.017***	-0.014***
		(0.008)	(0.008)		(0.004)	(0.004)
D_Brand x PPP_total		-0.002	0.004		0.009***	0.005***
		(0.005)	(0.005)		(0.002)	(0.002)
Ln_estab	-0.051***	-0.050***	-0.050***	0.002**	0.002**	0.002**
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
(SAH=1) x Ln_estab	-0.220***	-0.215***	-0.216***	0.049***	0.051***	0.051***
	(0.006)	(0.007)	(0.006)	(0.004)	(0.004)	(0.004)
(SAH=2) x Ln_estab	-0.111***	-0.106***	-0.108***	0.015***	0.015***	0.016***
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Ln_household	0.044***	0.044***	0.044***	-0.015***	-0.015***	-0.015***
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
(SAH =1) x Ln_household	0.192***	0.192***	0.192***	-0.064***	-0.064***	-0.064***
	(0.007)	(0.007)	(0.007)	(0.004)	(0.004)	(0.004)
(SAH =2) x Ln_household	0.112***	0.112***	0.112***	-0.027***	-0.027***	-0.027***
	(0.004)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)
Ln_nstore	-0.001	-0.001	-0.001	0.011***	0.011***	0.011***
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
(SAH =1) x Ln_nstore	0.006	0.007	0.006	0.010***	0.009***	0.010***
	(0.005)	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)
(SAH =2) x Ln_nstore	-0.013***	-0.010***	-0.013***	0.009***	0.008***	0.009***
	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
Constant	-0.523***	-0.514***	-0.509***	0.253***	0.266***	0.263***
	(0.012)	(0.014)	(0.014)	(0.005)	(0.006)	(0.006)
Observations	1,040,948	1,040,948	1,040,948	1,055,519	1,055,519	1,055,519
Store FE	No	No	No	No	No	No
County-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.275	0.274	0.275	0.0623	0.0621	0.0623

Table 5: The Effect of Small Business Lending

This table reports regression results to examine the effect of small business lending on foot traffic and store closing differential between brand stores and independent stores. The dependent variable is the change in the number of visits from the same month last year in Panel A and store closing in Panel B. We define store closing as an indicator variable equal to 1 if the store has fewer than 5 visits in that week or a decline of foot traffic for more than 90% and zero otherwise. D_Brand is an indicator variable that equals one if the store belongs to a brand and zero otherwise. SAH is an indicator variable that equals one if the state has issued a stay-at-home order during the week, two if the state has reopened for businesses following the stay-at-home order, and zero otherwise. D_SBL is an indicator variable the equals one if the measure of small business lending exposure is in the top quartile and zero otherwise. Ln_estab and Ln_household are the log of the number of business establishments and the log of the number of households in the zip code, respectively. Fixed effects included in each regression are indicated in the column. Standard errors clustered by county x week are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1%, respectively.

	Panel A: Change in # of Visits			Panel B: Store Closing		
	(1)	(2)	(3)	(1)	(2)	(3)
D_Brand	0.090***	0.087***		-0.055***	-0.057***	
	(0.003)	(0.004)		(0.001)	(0.001)	
(SAH=1) x D_Brand	0.220***	0.234***	0.228***	-0.076***	-0.081***	-0.083***
	(0.007)	(0.008)	(0.007)	(0.003)	(0.003)	(0.003)
(SAH=2) x D_Brand	0.101***	0.098***	0.103***	-0.034***	-0.033***	-0.029***
	(0.004)	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)
D_SBL	0.034***			-0.005***		
	(0.004)			(0.002)		
(SAH=1) x D_SBL	0.010			0.001		
	(0.009)			(0.005)		
(SAH=2) x D_SBL	0.014**			-0.013***		
	(0.006)			(0.003)		
D_SBL x D_Brand	-0.031***	-0.022***		0.012***	0.013***	
	(0.004)	(0.005)		(0.002)	(0.002)	
(SAH=1) x D_SBL x D_Brand	-0.017*	-0.032***	-0.016*	-0.002	-0.002	0.008**
	(0.010)	(0.011)	(0.009)	(0.004)	(0.005)	(0.004)
(SAH=2) x D_SBL x D_Brand	-0.005	-0.003	0.009	0.009***	0.005*	0.008***
	(0.006)	(0.007)	(0.007)	(0.002)	(0.003)	(0.003)
Ln_estab	-0.055***			0.004***		
	(0.002)			(0.001)		
(SAH=1) x Ln_estab	-0.165***			0.046***		
	(0.007)			(0.004)		
(SAH=2) x Ln_estab	-0.064***			0.013***		
	(0.004)			(0.001)		
Ln_household	0.044***			-0.013***		
	(0.003)			(0.001)		
(SAH =1) x Ln_household	0.150***			-0.049***		
	(0.007)			(0.004)		
(SAH =2) x Ln_household	0.066***			-0.012***		
	(0.005)			(0.002)		
Constant	-0.488***	-0.283***	-0.232***	0.237***	0.103***	0.066***
	(0.012)	(0.001)	(0.002)	(0.005)	(0.001)	(0.001)
Observations	1,040,948	876,506	876,506	1,055,519	891,221	891,221
Store FE	No	No	Yes	No	No	Yes
COUNTY-Week FE	Yes	No	No	Yes	No	No
ZIP-Week FE	No	Yes	Yes	No	Yes	Yes
Adjusted R-squared	0.275	0.301	0.519	0.0621	0.0610	0.378

Table 6: Brand vs. Independent Stores - Consumer Preference

This table reports regression results to examine consumer preference on the traffic differential between brand stores and independent stores. The dependent variable is the change in the number of visits from the same month last year (Panel A) or store closing (Panel B). We define store closing as an indicator variable equal to 1 if the store has fewer than 5 visits in that week or a decline of foot traffic for more than 90% and zero otherwise. For each panel, columns 1 to 3 use consumers' preferences for local stores, and columns 4 – 6 use online shopping experience. D_Local is an indicator variable that equals one if the percentage of respondents who prefer to shop in local stores is in the top quartile. D_AMZ is an indicator variable that equals one if the percentage of respondents who have shopped at Amazon.com in the last 30 days is in the top quartile and zero otherwise. D_Brand is an indicator variable that equals one if the store belongs to a brand and zero otherwise. SAH is an indicator variable that equals one if the state has issued a stay-at-home order during the week, two if the state has reopened for businesses following the stay-at-home order, and zero otherwise. Fixed effects included in each regression are indicated in the column. Standard errors clustered by county x week are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1%, respectively.

Panel A: Change in # of Visits

	Preference for Local Stores (D_Local)			Shopping at Amazon.com (D_AMZ)		
	(1)	(2)	(3)	(4)	(5)	(6)
D_Brand	0.078***	0.078***		0.080***	0.080***	
	(0.003)	(0.003)		(0.003)	(0.003)	
(SAH=1) x D_Brand	0.221***	0.228***	0.229***	0.212***	0.221***	0.218***
	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)	(0.006)
(SAH=2) x D_Brand	0.109***	0.101***	0.112***	0.099***	0.092***	0.099***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
D_Consumer	-0.015***			0.001		
	(0.005)			(0.005)		
(SAH=1) x D_Consumer	0.036***			-0.068***		
	(0.009)			(0.011)		
(SAH=2) x D_Consumer	0.018***			-0.026***		
	(0.006)			(0.008)		
D_Brand x D_Consumer	-0.003	-0.001		-0.010*	-0.011	
	(0.005)	(0.006)		(0.005)	(0.007)	
(SAH=1) x D_Consumer x D_Brand	-0.042***	-0.020*	-0.028***	0.001	0.008	0.025**
	(0.010)	(0.012)	(0.010)	(0.012)	(0.014)	(0.011)
(SAH=2) x D_Consumer x D_Brand	-0.033***	-0.016*	-0.023***	0.012	0.028***	0.037***
	(0.007)	(0.008)	(0.008)	(0.008)	(0.010)	(0.009)
Constant	-0.271***	-0.283***	-0.233***	-0.265***	-0.283***	-0.234***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
Observations	1,040,948	876,506	876,506	1,040,948	876,506	876,506
Store FE	No	No	Yes	No	No	Yes
CTY-Week FE	Yes	No	No	Yes	No	No
ZIP-Week FE	No	Yes	Yes	No	Yes	Yes
Adjusted R-squared	0.264	0.301	0.519	0.264	0.301	0.519

Panel B: Store Closing

	Preference for Local Stores (D_Local)			Shopping at Amazon.com (D_AMZ)		
	(1)	(2)	(3)	(4)	(5)	(6)
D_Brand	-0.054***	-0.053***		-0.049***	-0.050***	
	(0.001)	(0.001)		(0.001)	(0.001)	
(SAH=1) x D_Brand	-0.082***	-0.085***	-0.084***	-0.068***	-0.075***	-0.073***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
(SAH=2) x D_Brand	-0.032***	-0.031***	-0.026***	-0.030***	-0.029***	-0.024***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
D_Consumer	-0.006***			0.018***		
	(0.002)			(0.002)		
(SAH=1) x D_Consumer	-0.018***			0.045***		
	(0.004)			(0.006)		
(SAH=2) x D_Consumer	-0.003			0.013***		
	(0.003)			(0.003)		
D_Brand x D_Consumer	0.006***	0.008***		-0.015***	-0.010***	
	(0.002)	(0.002)		(0.002)	(0.003)	
(SAH=1) x D_Consumer x D_Brand	0.023***	0.009*	0.014***	-0.035***	-0.034***	-0.034***
	(0.004)	(0.005)	(0.004)	(0.006)	(0.007)	(0.005)
(SAH=2) x D_Consumer x D_Brand	0.006**	0.001	-0.000	-0.008**	-0.013***	-0.011***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Constant	0.105***	0.103***	0.066***	0.096***	0.104***	0.066***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	1,055,519	891,221	891,221	1,055,519	891,221	891,221
Store FE	No	No	Yes	No	No	Yes
CTY-Week FE	Yes	No	No	Yes	No	No
ZIP-Week FE	No	Yes	Yes	No	Yes	Yes
Adjusted R-squared	0.0580	0.0609	0.378	0.0589	0.0612	0.378

Table 7: Brand Stores vs. Independent Stores -Distribution Center

This table reports regression results to examine the differential between the brand and independent stores using a subsample, including independent stores and CVS as the only brand store. For all CVS stores, we identify the closest warehouse (in distance) using addresses of CVS's corporate distribution centers. Close_to_Warehouse is an indictor variable if the closest distribution center is within 50 miles, and zero otherwise. Busy_Warehouse is an indicator equal to one if the number of stores a distribution center has within 100 miles falls in the top quartile across all distribution centers. The dependent variable is the change in the number of visits from the same month last year. D_Brand is an indicator variable that equals one if the store belongs to a brand and zero otherwise. SAH is an indicator variable that equals one if the state has issued a stay-at-home order during the week, two if the state has reopened for businesses following the stay-at-home order, and zero otherwise. Fixed effects included in each regression are indicated in the column. Standard errors clustered by county x week are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)
DEP VAR = Change in the # of Visits				
D_Brand	0.080***	0.079***		
	(0.004)	(0.004)		
(SAH=1) x D_Brand	0.191***	0.196***	0.202***	0.208***
	(0.010)	(0.010)	(0.008)	(0.008)
(SAH=2) x D_Brand	0.102***	0.101***	0.122***	0.121***
	(0.006)	(0.006)	(0.005)	(0.005)
D_Brand x Close_to_Warehouse	-0.003	-0.011		
	(0.008)	(0.009)		
(SAH=1) x D_Brand x Close_to_Warehouse	0.044***	0.063***	0.028**	0.048***
	(0.015)	(0.017)	(0.013)	(0.014)
(SAH=2) x D_Brand x Close_to_Warehouse	0.016	0.014	-0.001	-0.004
	(0.010)	(0.011)	(0.009)	(0.010)
D_Brand x Busy_Warehouse		0.031***		
		(0.010)		
(SAH=1) x D_Brand x Busy_Warehouse		-0.057***		-0.053***
		(0.020)		(0.016)
(SAH=2) x D_Brand x Busy_Warehouse		0.012		0.009
		(0.014)		(0.013)
Constant	-0.285***	-0.285***	-0.252***	-0.252***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	438,942	438,942	438,942	438,942
Store FE	No	No	Yes	Yes
ZIP-Week FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.268	0.268	0.496	0.496

Table 8: Robustness Checks - Controlling for Nearby Medical Offices

This table reports regression results to examine the differential between the brand and independent stores, controlling for medical offices nearby. We control for medical offices (3-digit NAICS code in 621, 622, and 623) in the 100-yd radius (Panel A) or 200-yd radius (Panel B). The dependent variable is the change in the number of visits from the same month last year. D_Brand is an indicator variable that equals one if the store belongs to a brand and zero otherwise. SAH is an indicator variable that equals one if the state has issued a stay-at-home order during the week, two if the state has reopened for businesses following the stay-at-home order, and zero otherwise. D_Medical is an indicator equal to 1 if there are medical offices nearby and zero otherwise. Fixed effects included in each regression are indicated in the column. Standard errors clustered by county x week are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1%, respectively.

	Panel A: Within 100 yds			**Panel B: Within 200 yds**		
	(1)	(2)	(3) Excl. if D_Medical=1	(1)	(2)	(3) Excl. if D_Medical=1
DEP VAR = Change in the # of Visits						
D_Brand	0.078***			0.081***		
	(0.003)			(0.003)		
(SAH=1) x D_Brand	0.216***	0.214***	0.214***	0.216***	0.212***	0.212***
	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
(SAH=2) x D_Brand	0.097***	0.105***	0.104***	0.094***	0.101***	0.099***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
D_Medical	-0.005			0.008*		
	(0.006)			(0.005)		
(SAH=1) x D_Medical	-0.110***	-0.120***		-0.073***	-0.083***	
	(0.013)	(0.011)		(0.010)	(0.008)	
(SAH=2) x D_Medical	-0.002	-0.011		-0.010	-0.019***	
	(0.009)	(0.008)		(0.007)	(0.006)	
D_Brand x D_Medical	-0.012			-0.018***		
	(0.008)			(0.005)		
(SAH=1) x D_Brand x D_Medical	-0.002	-0.000		0.007	0.017	
	(0.017)	(0.015)		(0.013)	(0.010)	
(SAH=2) x D_Brand x D_Medical	-0.002	0.001		0.014*	0.020***	
	(0.012)	(0.011)		(0.008)	(0.007)	
Constant	-0.280***	-0.230***	-0.222***	-0.281***	-0.227***	-0.208***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Observations	876,506	876,506	818,712	876,506	876,506	705,241
Store FE	No	Yes	Yes	No	Yes	Yes
ZIP-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.301	0.520	0.512	0.301	0.520	0.504

Table 9: Robustness Checks - Testing Center and In-Store Clinics

This table reports regression results to examine the differential between the brand and independent stores using a subsample, including all independent stores and CVS as the only brand store, controlling for testing centers (Panel A) or in-store clinics (Panel B). The dependent variable is the change in the number of visits from the same month last year. D_Brand is an indicator variable that equals one if the store belongs to a brand and zero otherwise. SAH is an indicator variable that equals one if the state has issued a stay-at-home order during the week, two if the state has reopened for businesses following the stay-at-home order, and zero otherwise. D_Testing is an indicator variable equal to one if the store offers COVID testing during that week and zero otherwise. D_Clinic is an indicator variable equal to one if the store has an on-site clinic and zero otherwise. D_Large is an indicator variable equal to one if the store size is in the top quartile and zero otherwise. Fixed effects included in each regression are indicated in the column. Standard errors clustered by county x week are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1%, respectively.

Panel A: Testing Centers

	(1)	(2)	(3)
DEP VAR = Change in the # of Visits			Excl. if D_Testing=1
D_Brand	0.079***		
	(0.004)		
(SAH=1) x D_Brand	0.217***	0.218***	0.219***
	(0.008)	(0.007)	(0.007)
(SAH=2) x D_Brand	0.097***	0.113***	0.114***
	(0.005)	(0.005)	(0.005)
D_Brand x D_Testing	0.064***	0.040***	
	(0.005)	(0.005)	
Constant	-0.285***	-0.252***	-0.254***
	(0.001)	(0.001)	(0.001)
Observations	438,942	438,942	406,897
Store FE	No	Yes	Yes
ZIP-Week FE	Yes	Yes	Yes
Adjusted R-squared	0.268	0.496	0.500

Panel B: In-Store Clinics

DEP VAR = Change in the # of Visits	(1)	(2)	(3)	(4)
D_Brand	0.081***		0.075***	
	(0.004)		(0.004)	
(SAH=1) x D_Brand	0.218***	0.220***	0.199***	0.201***
	(0.008)	(0.007)	(0.008)	(0.007)
(SAH=2) x D_Brand	0.109***	0.119***	0.105***	0.118***
	(0.005)	(0.005)	(0.005)	(0.005)
D_Brand x D_Clinic	-0.017***		-0.017***	
	(0.005)		(0.005)	
(SAH=1) x D_Brand x D_Clinic	-0.015	-0.016*	-0.017*	-0.018*
	(0.010)	(0.009)	(0.010)	(0.009)
(SAH=2) x D_Brand x D_Clinic	0.014**	0.014**	0.014**	0.014**
	(0.007)	(0.006)	(0.007)	(0.006)
D_Large			-0.024***	
			(0.006)	
(SAH=1) x D_Large			-0.053***	-0.057***
			(0.012)	(0.010)
(SAH=2) x D_Large			-0.031***	-0.025***
			(0.009)	(0.008)
D_Brand x D_Large			0.035***	
			(0.009)	
(SAH=1) x D_Brand x D_Large			0.106***	0.107***
			(0.017)	(0.015)
(SAH=2) x D_Brand x D_Large			0.020	0.006
			(0.012)	(0.012)
Constant	-0.285***	-0.252***	-0.277***	-0.249***
	(0.001)	(0.001)	(0.001)	(0.002)
Observations	438,942	438,942	438,942	438,942
Store FE	No	Yes	No	Yes
ZIP-Week FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.268	0.496	0.268	0.496

Table 10: Brand vs. Independent Stores - Nearby Stores

This table reports regression results to examine the differential between stores near the brand and independent drug stores. For each drug store (brand or independent), we search for establishments in a 200-yd or 500-yd radius. Panel A examines the initial foot traffic (measured as the log of the number of visits in January 2020). Panel B examines the change in the number of visits from the same month last year. D_Brand is an indicator variable that equals one if the store belongs to a brand and zero otherwise. SAH is an indicator variable that equals one if the state has issued a stay-at-home order during the week, two if the state has reopened for businesses following the stay-at-home order, and zero otherwise. Fixed effects included in each regression are indicated in the column. Standard errors clustered by county x week are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1%, respectively.

	Panel A: Initial Traffic			Panel B: Changes in Foot Traffic		
	(1)	(2)	(3)	(1)	(2)	(3)
VARIABLES	Nearby Stores (200-yd)	Nearby Stores (500-yd)	Drug Store (our sample)	Nearby Stores (200-yd)	Nearby Stores (500-yd)	Drug Store (our sample)
D_Brand	0.384***	0.288***	1.013***			
	(0.020)	(0.014)	(0.020)			
(SAH=1) x D_Brand				0.093***	0.074***	0.222***
				(0.005)	(0.003)	(0.005)
(SAH=2) x D_Brand				0.058***	0.049***	0.102***
				(0.003)	(0.002)	(0.004)
Constant	5.229***	5.510***	4.984***	-0.337***	-0.356***	-0.230***
	(0.014)	(0.010)	(0.014)	(0.001)	(0.001)	(0.002)
Observations	20,112	22,269	22,269	774,348	863,356	850,510
Store FE				Yes	Yes	Yes
ZIP-Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.153	0.303	0.316	0.680	0.824	0.524

Table 11: Brand vs. Independent Stores - The Size Effect

This table reports regression results to examine the differential between the brand and independent stores in different size categories. The dependent variable is the change in the number of visits from the same month last year. D_Brand is an indicator variable that equals one if the store belongs to a brand and zero otherwise. SAH is an indicator variable that equals one if the state has issued a stay-at-home order during the week, two if the state has reopened for businesses following the stay-at-home order, and zero otherwise. Size is an indicator variable that equals one if the store is in the top quartile by initial visits in January 2020 (column 1-2) and by square footage (column 3-4). Fixed effects included in each regression are indicated in the column. Standard errors clustered by county x week are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1%, respectively.

DEP VAR = Change in # of Visits	(1) Initial Visits	(2) Initial Visits	(3) Store Size	(4) Store Size
D_Brand	0.079***		0.074***	
	(0.003)		(0.003)	
(SAH=1) x D_Brand	0.220***	0.219***	0.206***	0.202***
	(0.007)	(0.006)	(0.007)	(0.006)
(SAH=2) x D_Brand	0.105***	0.112***	0.094***	0.104***
	(0.004)	(0.004)	(0.004)	(0.004)
D_Large	0.067***		-0.018***	
	(0.007)		(0.005)	
(SAH=1) x D_Large	-0.135***	-0.152***	-0.034***	-0.050***
	(0.012)	(0.011)	(0.010)	(0.009)
(SAH=2) x D_Large	-0.231***	-0.253***	-0.028***	-0.029***
	(0.011)	(0.009)	(0.008)	(0.007)
D_Brand x Size	-0.058***		0.019***	
	(0.007)		(0.006)	
(SAH =1) x D_Brand x D_Large	0.115***	0.131***	0.074***	0.090***
	(0.013)	(0.012)	(0.011)	(0.010)
(SAH =2) x D_Brand x D_Large	0.163***	0.187***	0.021**	0.019**
	(0.011)	(0.009)	(0.009)	(0.008)
Constant	-0.278***	-0.223***	-0.276***	-0.229***
	(0.001)	(0.002)	(0.001)	(0.002)
Observations	876,506	876,506	876,506	876,506
Store FE	No	Yes	No	Yes
ZIP-Week FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.302	0.520	0.301	0.519