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

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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. The reduction in demand was greatest in business districts and in higher-income areas. The shock was accompanied by a shift of customers from small independent businesses to brand stores, most strongly in the suburbs. The composition of customers changed, with brand stores, in particular, serving a more local customer base. PPP and the presence of small-business-friendly banks in the same zip code only partly mitigate the shift to brands. The effect of PPP loans and financial access is higher in low-income areas and varies significantly across geographies reflecting different local shocks to demand. More broadly, the COVID-19 pandemic accelerated the ongoing reallocation of market share in local markets from independent businesses to brands, in particular for large stores. If the new working from home patterns do not reverse, the growth of brands relative to small businesses will reduce the role of small businesses in this sector.

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 business. 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 moving demand from locations where small independent stores have a strong presence to locations where national brands have a comparative advantage.[2]

In this paper, we ask four questions: How badly have small retail businesses been hit? How are those hits distributed across the country? How well did government programs work to help small businesses? What effect do these shocks have on the competitive struggle between large scale brands and small business providers? Using Safegraph establishment-level mobility data that gives us near real-time measures of foot-traffic in retail establishments, Nielsen data on consumer preferences, and Census Bureau administrative data at zip code

[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 tends in our lifetime: consolidation and inequality," "The end of small business." *Washington Post*, July 9, 2020.

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 32,195 stores in 12,308 unique zip code from 2,727 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 differences in the effect of COVID-19 on foot-traffic across localities. The drop in foot-traffic was the greatest in high-income areas, business districts, and suburbs. It is lowest in rural areas and small towns. Controlling for zip-week effects, we find that foot traffic is uniformly less affected in pharmacies owned by national brands, particularly the large stores owned by brands. Large independent pharmacies are particularly hard hit, especially in low-income areas and urban areas. However, market share and comparative advantage of small businesses and nationally branded stores vary across locations. The move towards brands is largest in high-income areas. It is particularly strong in the suburbs, reverses in business districts, and is weaker in urban and rural areas. Thus, the shock and the concomitant reallocation of demand has had a strong negative effect on independent pharmacies, particularly in high income and suburban areas.

There have been multiple attempts to aid businesses through the PPP loan program.[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. Instrumenting using the distribution of the local bank branches and banks' national share of PPP loans, we find that the amount of PPP causes the foot traffic differential between brand and independent pharmacies to shrink. This indicates that the cash infusion from the PPP helped independent pharmacies compete with brand pharmacies. However, the economic effect is relatively modest, 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.

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

is associated with the recovery of about 10 percent of the gain by brand stores relative to independents. The effect of PPP loans received varies by geography and is only significant in high income zips.

We also examine the role of the banking at 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 of banks that engage in substantial small business lending predicts relatively better outcomes for independent stores. The effects of prior relationships were present in all zip codes except the highest income quartiles, and in urban and business districts. In suburbs, we found that small-business-friendly banks were associated with a relative increase in brand foot store traffic. This finding is consistent with the hypothesis that small-business-friendly banks support other small businesses, whose employees, workers, and customers prefer to patronize brand pharmacies. Overall, we find that the effect of prior banking relationships is statistically significant but economically moderate in reducing the gap between brands and independents.

To summarize, the COVID-19 shock shuffled retail demand across localities. For pharmacies, it resulted in large drops in foot traffic in business districts, urban areas, and high income areas. Overall, brand stores benefited from this shift in demand. The PPP and small business-friendly local banks only partially offset gains by brands.

We provide further evidence on the nature of the real shock that changed demand patterns. First, we find that the preference for brands is greatest in suburbs and least in business districts. Second, the shift is smallest in zip codes in which consumers indicated on prior surveys a preference for local stores. Consistent with that observation, in zip codes in which more consumers indicated that they shopped on Amazon, brands realized higher gains over independent pharmacies. Third, the greatest shift is from large independent to large brand stores, consistent with the conjecture that these stores are direct substitutes and that brands have a comparative advantage in managing large stores. Fourth, tracking customers in brand stores and independent stores, we find that, as expected, consumers

shop closer to their homes during the COVID crisis, and the decline in distance in distance is greater for brand stores.

Taken together, evidence suggests a shift in demand for brand stores. Independent stores have been affected particularly hard when store traffic moved away from urban business districts to suburban residential areas, where consumers were more likely to shop in brand pharmacies even before the pandemic hit. Independents continue to do comparatively well in business districts, but these localities do worse overall.If the trend to working from home is not reversed, local retail markets will be reshaped, especially in suburbs and business districts, likely accelerating the rise of brands and the decline of small businesses.[5]

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 are 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-market firms between 1997 and 2003 as they move into more locations previously served by independent firms. Our paper places these developments in the colier (1995) and ntext 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

[5]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.

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) in the U.S on the number of visits and information about visitors. 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. 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 keep the measurement manageable.[6] We have 32,195 stores in 12,308 unique zip code from 2,727 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 July 13, 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.

[Insert Figure 1 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).[7] For states that did not issue statewide stay-at-home orders, we code the variable equal to zero. We collect zip code level 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. Figure 3 shows changes in foot traffic over time for the brand- and independent stores over the four household income quartiles. Low-income areas see a smaller decline in foot traffic to pharmacies and drug stores, and also a small gap between brand and independent stores. 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. Figure 3 shows changes in foot traffic over time for brand- and independent stores in business and non-business districts. Interestingly, although brand stores do better

[6] SafeGraph reports that their algorithm records approximately 10% of all visits.
[7] https://www.nytimes.com/interactive/2020/us/states-reopen-map-coronavirus.html

in non-business districts in general, they do worse in business districts.

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.[8] 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.[9] 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 presents the summary statistics of our sample. Brand stores are bigger and have more foot traffic. About 61% 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 the suburbs (28 % vs. 17% for independent stores) whereas independent stores are more likely to be in small towns (50% vs. 34%). Brand stores are in higher income locations ($78,191 vs $68,775), with higher mean number of banks in their zip codes.[10] Both brand stores and independent stores have a similar percentage of small business friendly bank branches in their zip codes.

[Insert Table 1 Here]

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

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

[10] 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.

3 Empirical Results

3.1 The General Effect of COVID

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 62 percent under statewide stay-at-home mandates, and 39 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 54 percent and 40 percent, respectively, during the stay-at-home period 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.

[Insert Table 2 Here]

During the same time, consumers significantly decrease the radius of their shopping areas. 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 12 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.[11] Urban and suburban zip codes also report greater than county average declines, consistent with a decrease in shopping-related commuting and leisure travel.

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

3.2 Brand vs. Independent Stores

Table 3 Panel A presents the relative difference in foot traffic between brand and independent stores. Column 1 shows that before the pandemic brand stores experienced a precisely estimated 7.6 percent higher year-to-year growth relative to independent stores in the same country or zip code. 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). To control for the pre-trend between brand and independent stores, we include a store fixed effect for all the remaining columns. In columns 2 - 7, 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 brand and independent stores. COVID had a significant adverse effect on the market shares of independent stores. Brands have significantly smaller losses in foot traffic during COVID, relative to independent stores in the same country or zip code. Foot traffic is 26 percentage points higher in brand stores during the stay-at-home period, more than 40 percent of the total loss. The difference becomes smaller to 9.2 percentage points (about 24 percent of the total loss) after states reopened for business.

[Insert Table 3 Here]

Figure 2 presents the year-to-year change in foot traffic for brand stores and independent stores by week. The aggregate gap is at its height in the middle of April, before states began to reopen for business and then narrows, with a 10 percentage point differential at the end of our sample.

[Insert Figure 2 Here]

Across different locations, brand stores do relatively better in suburbs and second city zip codes, and worse in urban and town and rural 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.

To understand the reallocation of demand over the pandemic period, in Table 3 Panel B we examine the change in distance from home an average customer travels to shop. We

find that during the pandemic, consumers to brand stores come from more close-by areas, relative to customers who shop in independent stores. This effect is more significant in urban areas, and especially so 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.

In Figure 3A-C, we present changes in store traffic over time between the brand and independent stores across income levels, locations, and business districts, respectively.

[Insert Figure 3A, 3B, and 3C Here]

The gap between brand and independent stores is larger in the top income quartile zip-codes than in bottom income quartile zip-codes. Location wise, the gap is bigger in suburbs where independent stores were particularly hard hit. The differential is relatively small in small towns and rural areas. Of particular interest is Figure 3C, which compares brands and independents in business districts and other locations. In contrast to the breakdowns, we see that brands in business districts do considerably worse. This is consistent with a geographic reallocation of demand by relatively high income consumers who used to shop in brand stores from areas surrounding their workplaces moving to other locations.

Figure 4 relaxes the definition of business districts and examine changes in the number of visits and changes in distance traveled by customers across five groups ranked by the business-residential ratio.[12] We find a monotone effect – drops in foot traffic are bigger in more business-oriented areas, and so are losses from out-of-area shoppers. In Figure 5, we compare the median distance traveled by shoppers before and during the COVID pandemic. Business districts and urban zip codes have more far-away visitors before COVID and lost more of them during COVID.

[Insert Figure 4 and Figure 5]

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

[12]We define business districts as zip codes with business employment over residential population ratio greater than two for most tables in our paper.

of independents relative to brands by Hsieh and Rossi-Hansberg (2020). The COVID shock is associated with an economically significant increase in this differential. The increase is general, but has distinctive geographical properties. It is particularly strong in high income areas and in 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 are 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 the majority of the loans distributed by May 3, 2020.

We obtain the loan-level data on PPP from the website of the U.S. Department of the Treasury. Firm information is not available for loans less than $150,000 for privacy protection. For loans greater than $150,000, data is only available for the loan range, not the actual amount.[13] So, we use the midpoint of the loan range as an estimate. Close to half of the zip codes in our sample have received at least one PPP loan for pharmacies and drug stores. Conditional on receiving PPP loans, 68 percent received one loan, 19 percent received two loans, and fewer than 2 percent of zip codes received more than five loans. The average loan size is around $140,000, and the median loan size is $75,000. We aggregate the total amount of PPP loans approved for pharmacies for each zip code by week, and the use the cumulative amount in the week before as our measure (PPP). It captures the

[13] Loan ranges are $150K-$350K, $350k-$1M, $1M-$2M, $2M-$5M, and $5M-$10M.

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. Both help 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 existence of spillovers, 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 (D_PPP_Total). Table 4 presents our findings.

[INSERT TABLE 4 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, Column 1 to 3 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 and the number of business establishments 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 4.3 percent more foot traffic, compared to 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 the size of their firms, our results suggest that targeted PPP loans help independent drug stores to catch up with their brand counterparts. In contrast, column 2 shows that the total PPP loans in the zip code do not seem to have a significant effect on drug stores, nor do they lead to any differential effect between brand and independent stores. Our results are robust when we include both industry PPP and total PPP loans in column 3. In column 4 to 6, we include $zip \times week$ fixed effects to control for differences in zip codes that are not captured by our control variables. Since the PPP measure is calculated at the zip code, we can no longer estimate the main effect

of the PPP. As before, we see that both industry and total PPP loans are less beneficial to brand stores. In particular, controlling more precisely at the zip level suggests that total PPP loans to a zip code may, at the margin, have a spillover effect by bringing in additional customers who shop at independent stores. The magnitude of the combining effect from both industry and total PPP loans, however, is small (around 2.9%) - one-quarter of the estimated difference between the brand and independent stores after reopening (11.7%). Panel B presents our results using the continuous version of the PPP variables (log of the loan amount). Results are qualitatively similar.[14]

Next, we examine the differential effect of PPP loans for drug stores on brand and independent stores by zip code characteristics, including income levels and locations. Table 5 present our results.

[INSERT TABLE 5 HERE]

Panel A shows that although there is a consistent negative effect across many income levels, our result of independent stores benefiting more from PPP loans is mostly driven by the top income quartile zip codes. Recall that independent stores tend to do much worse than brand stores in high-income zip codes during the pandemic period. So, our finding suggests that PPP loans help to mitigate the gap between brand and independent stores in areas when independent stores are at a bigger disadvantage. The same pattern holds in Panel B. PPP helps independent stores in suburbs where they suffer the worst shocks. Consistent with that finding, we find no evidence that PPP helps independent stores relative to brands in areas where independent stores are relatively strong (cities and towns).[15] We find that independent stores also benefit from PPP loans in urban areas and business districts.

A potential concern with our analysis of the effect of PPP loans is that omitted variables can drive both the traffic differential between brand stores and independent stores and PPP loans. To address this concern, we develop an instrumental variable strategy. We

[14] For robustness check, we rerun the same specification for periods immediately followed by the completion of the first and the second tranche of PPP loans. Results are qualitatively the same.

[15] As previous tables and figures show, independent stores are relatively strong in towns. Interestingly, in small towns and rural areas, we find that PPP loans to local pharmacies are associated with higher foot traffic for brand firms. While subject to further analysis, one possibility is that this result arises from competitive interactions between brands and independents in towns, with brands aggressively responding to locally strong high market share independents.

construct a Bartik-type instrument to estimate the local exposure to PPP loans by interacting branches located in the zip code and banks' national share of PPP loans. Bartik et al. (2020b) show that approval rates vary widely across banks. We follow their approach to include indicator variables for branches of the top 4 banks or the top 5-10 banks in the zip code. We identify all bank branches in each zip code using the Summary of Deposits (SOD) from the FDIC and use the list of top 1-4 banks and top 5-10 banks provided by Bartik et al. (2020b). We use the national share of PPP in the top 20 banks provided in Granja et al. (2020). Table 6 presents our regression estimates. Similar to what's reported in the OLS regressions in Table 4, we find that money from PPP managed to help drug stores in the zip code to increase foot traffic, with a differential effect on independent stores. We find a Kleibergen-Paap (2006) F-statistics value of 17.3, comfortably rejecting the null that the instruments are not relevant in the first stage. Notably, the estimated effect in the IV regression is substantially larger than the corresponding OLS estimates.

[Insert Table 6 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 median distance from the firm 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, and 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.[16] 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 the number of bank branches (D_Banks) or small business lending activities (D_SBL).

Table 7 report our findings. Column 1 shows that zip codes with more small business lending activities have a 2.3 percent higher growth in foot traffic even before the COVID-pandemic. The effect is bigger during the pandemic (3.0 percent). Interestingly, the effect is entirely on independent stores. Small business lending has no effect on brand stores[17].

[INSERT TABLE 7 HERE]

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

[17] The combined effect for brand stores is 2.3% - 2.0% = 0.3% before the pandemic, and is 3.0% -3.3% = -0.3% during the stay-at-home period

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. Since our measure of small business lending is related to the number of banks in the area, we control for the number of banks in column 4 (D_Banks). Our estimated coefficients suggest that it is the small business lending intensity, rather than the number of banks that help local stores. Interestingly, the presence of small-business-friendly banks is significant early in the crisis, and not significant in the second period.

Next, we examine the differential effect of small business lending on brand and independent stores by income levels and across different locations. Table 8 present our results.

[INSERT TABLE 8 HERE]

Panel A shows that the positive effect of small-business friendly banks on independent stores (over brand stores) is present in the first three income quartiles. Since brand stores attract more consumers in the top income quartile, the lack of effect from small business lending can be due to strong consumer preference for brand stores in those areas. Panel B shows that the effect is stronger in urban areas, but reverses in suburbs. There are several plausible explanations for the positive coefficient in suburbs. The most straightforward explanation is that the indirect effects of small business lending in these zips are sufficiently greater for brand pharmacies, which do much better in suburbs overall, than for independent pharmacies.[18] Panel C further reveals that although the presence of banks friendly to small business lending helps independent stores in both business and non-business districts, the effect is much more economically significant in business districts.

[INSERT TABLE 8 HERE]

4 Mechanisms

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

[18] We are in the process of exploring these interactions.

4.1 The Size Effect

Table 1 shows that brand stores are bigger - on average, a brand pharmacy has 37% more space than an independent pharmacy. How does size affect the differential between brand and independent stores during the COVID-pandemic?

We define large pharmacies as stores that are in the top size quartile (*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. One concern with the results reported so far might be that the preference for brand stores we have documented might be proxying for an omitted variable, a general preference for large stores. Table 9 Column 1 shows that this is not the case. Large stores had a lower growth before the pandemic and experienced bigger declines in store traffic during the pandemic. The pattern is reversed for brand pharmacies – large brand stores do better than other brand stores.

The high performance of large brand stores over large independent stores and smaller brand stores, both before the pandemic and during it, is of independent interest. It is consistent with the hypothesis that the comparative advantage of brand pharmacies over independent stores is in the management of large stores, which are more complex, given a broader range of product lines. This is consistent with the arguments of Hsieh and Rossi-Hansberg (2020) that what they term "the industrial revolution in services" is driven by brands' investments in ICT and technological advantages of providing complex standardized services at multiple locations.

4.2 Consumer Preference

One possible explanation for the observed differential in store traffic between 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 measures for consumer preference. The survey mea-

sures 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 that 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 the top quartile of our sample. Table 10 present our results.

[Insert Table 10 Here]

Panel A examines the effect of consumer preference for local shopping on the relative performance between brands and independents. Column 1 shows that pharmacies in areas the have a strong preference for local stores have slower growth before the pandemic but also experience a smaller decline during the pandemic. Moreover, when there is a strong preference for local stores, the difference between brand and independent stores. The estimated coefficient for the interaction term is 6.4%, about 25 percent of the differential between brands and independents, as documented in Table 3.[19] 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 a significant part of the differences in store traffic between brands and independents is driven by differences in taste.

In Panel B, we examine how consumers' experience in online shopping 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. However, experiences in online shopping do not seem to explain the differential in response between the brand and independent stores documented in earlier tables. Areas where consumers shop on Amazon experienced a bigger difference between brand and independent

[19] 6.4%/25.9%.

stores.

Thus, while the growth of online shopping may affect the total foot traffic in stores, it does not affect the breakdown between brand and independent shopping in brick-and-mortar stores analyzed in this paper. In a broader sense, however, 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.

5 Conclusion

The COVID pandemic transformed retail markets across the U.S. The demand shock arrived in markets where small independent stores were under growing competitive pressure from large national chains. The demand shock reduced foot-traffic across the board, but reductions were uneven, affecting some locations such as business districts and high income areas more than rural areas.

Using very granular real-time measures of foot traffic at the establishment level in pharmacies, we show that as demand was reallocated, the national chains gained customers relative independent stores in most locations. This shift is most evident in larger brand stores, where large brand stores outperformed both large independent stores and small brand stores. Since large stores provide a broader range of services, our findings are consistent with analyses of technological trends in service markets, which have argued that large chains' advantages in ICT and coordination facilitate superior performance.

The preservation and growth of small businesses is a U.S. government policy objective. 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. However, this effect was partial. These stores made up about a quarter or so of the loss of foot-traffic to brand stores.

We also find that the composition of the local banking market significantly affects the 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 such banks in the same zip code 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. We find that the presence of small-firm-friendly is 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 the competitive response of small businesses.

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 has 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. To the extent that the working at home patterns partially persist after the epidemic shock has worn off, this will translate into a permanent shift of demand to brand pharmacies, which are more focused in suburban areas.

Amid falling business entry rates, small retail and service businesses have been a bright point in the reallocation of less qualified labor from manufacturing industries. If the reallocation in the response of COVID that we observe in retail pharmacies 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.

References

Agarwal, Sumit, and Robert Hauswald, 2010, Distance and Private Information in Lending, Review of Financial Studies, Volume 23, 2757-2788.

Bartik, Alexander, Bertrand, Marianne, Cullen, Zoe, Glaeser, Edward L., Luca, Michael and Stanton, Christopher, 2020a, How are Small Businesses Adjusting to COVID-19? Early Evidence from a Survey, University of Chicago, Becker Friedman Institute for Economics Working Paper No. 2020-42.

Bartik, Alexander W., Zoe B. Cullen, Edward L. Glaeser, Michael Luca, Christopher T. Stanton, and Adi Sunderam, 2020b, The Targeting and Impact of Paycheck Protection Program Loans to Small Businesses, NBER Working Paper No. 27623.

Black, SE and Phillip E. Strahan, 2002, Entrepreneurship and bank credit availability, Journal of Finance 57, 2807-2833.

Brevoort, Kenneth P.; Holmes, John A., and John D. Wolken, 2010, Distance still matters: the information revolution in small business lending and the persistent role of location, 1993-2003" Board of Governors of the Federal Reserve System Finance and Economics Discussion Series Working Paper No. 2010-08.

Cetorelli, Nicola, and Philip E. Strahan, 2006, Finance as a Barrier to Entry: Bank Competition and Industry Structure in Local U.S. Markets, Journal of Finance, 437-462.

Chen Brian S., Samuel G. Hanson, and Jeremy C. Stein, 2017,The Decline of Big-Bank Lending to Small Business: Dynamic Impacts on Local Credit and Labor Markets, NBER Working Paper No. 23843.

Chetty, R., Friedman, J.N., Hendren, N. and Stepner, M., 2020. How did covid-19 and stabilization policies affect spending and employment? a new real-time economic tracker based on private sector data", (No. w27431). National Bureau of Economic Research

Chevalier, J., 1995, Capital structure and product-market competition: Empirical evidence from the supermarket industry,The American Economic Review, 415-435.

Decker, Ryan A., John Haltiwanger, Ron Jarmin, and Javier Miranda (2014) The Role of Entrepreneurship in US Job Creation and Economic Dynamism, Journal of Economic Perspectives, Vol. 28, No. 3, pp. 3–24.

Gilje, EP, 2019, Does Local Access to Finance Matter? Evidence from US Oil and Natural Gas Shale Booms, Management Science, Volume: 65 1-18.

Granja, J., Makridis, C., Yannelis, C. and Zwick, E., 2020. Did the Paycheck Protection Program Hit the Target? (No. w27095). National Bureau of Economic Research

Guiso, L., Sapienza, P. and L. Zingales, 2004, Does local financial development matter? Quarterly Journal of Economics 119, 929-969.

Hsieh, Chang-Tai and Esteban Rossi-Hansberg (2020) The Industrial Revolution In Services, http://www.princeton.edu/ erossi/IRS.pdf

Hurst, E., and Pugsley, B. W. 2011. What do Small Businesses Do? Brookings Papers on Economic Activity, 43(2), 73-142.

Karahan, F., B. Pugsley, and A. Sahin. 2015. "Understanding the 30-year Decline in the Startup Rate: A General Equilibrium Approach." Working paper

Kerr, William and Ramana Nanda, 2009, Democratizing entry: Banking deregulations, financing constraints, and entrepreneurship, Journal of Financial Economics 94, 124-149.

Khanna Naveen, and Sheri Tice, 2001, The bright side of internal capital markets, The Journal of Finance 56 (4), 1489-1528 307 2001.

Khanna Naveen, and Sheri Tice, 2003, Strategic responses of incumbents to new entry: The effect of ownership structure, capital structure, and focus, The Review of Financial Studies 13 (3), 749-779.

Laderman, Elizabeth S. 2008. "The quantity and character of out-of-market small business lending." Federal Reserve Bank of San Francisco Economic Review : 31-39.

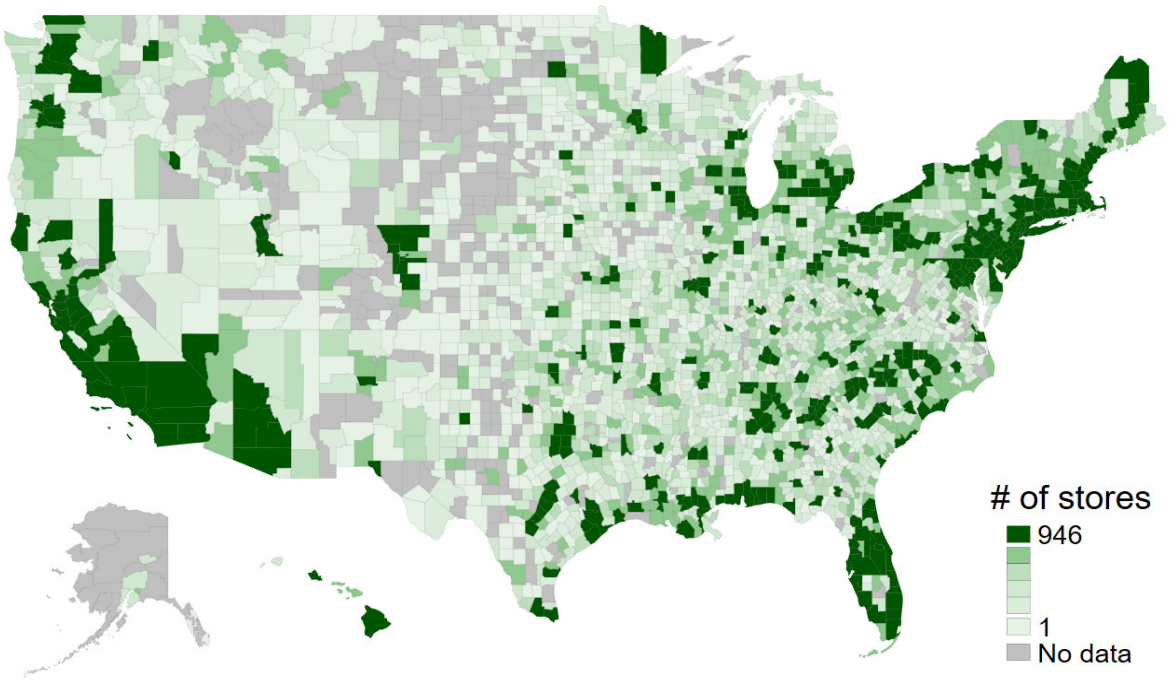
Nguyen Hoai-Luu Q, 2019. Are credit markets still local? Evidence from bank branch closings, American Economic Journal: Applied Economics 11, 1-32.

Smith, D., and S. Ocampo, 2020, The Evolution of U.S. Retail Concentration, BLS Working Papers No. 526, U.S. Department of Labor.

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

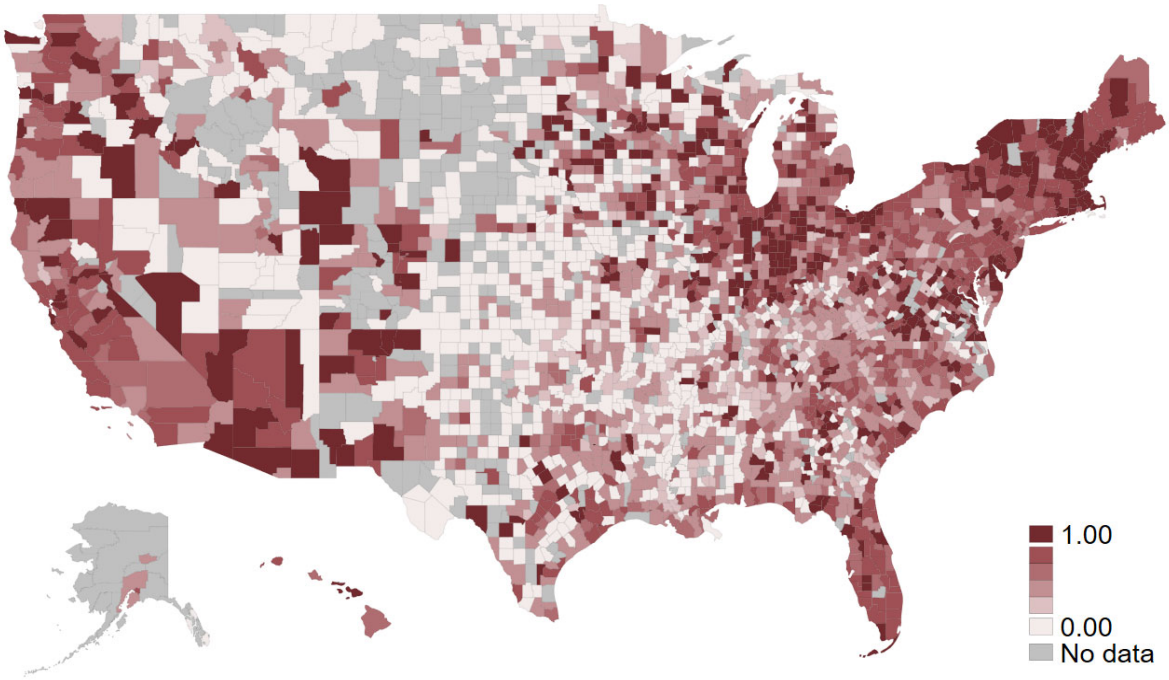


Figure 2: Change in Foot Traffic Over Time

This figures shows the average change in number of visits over our sample period for brand stores and independent stores.

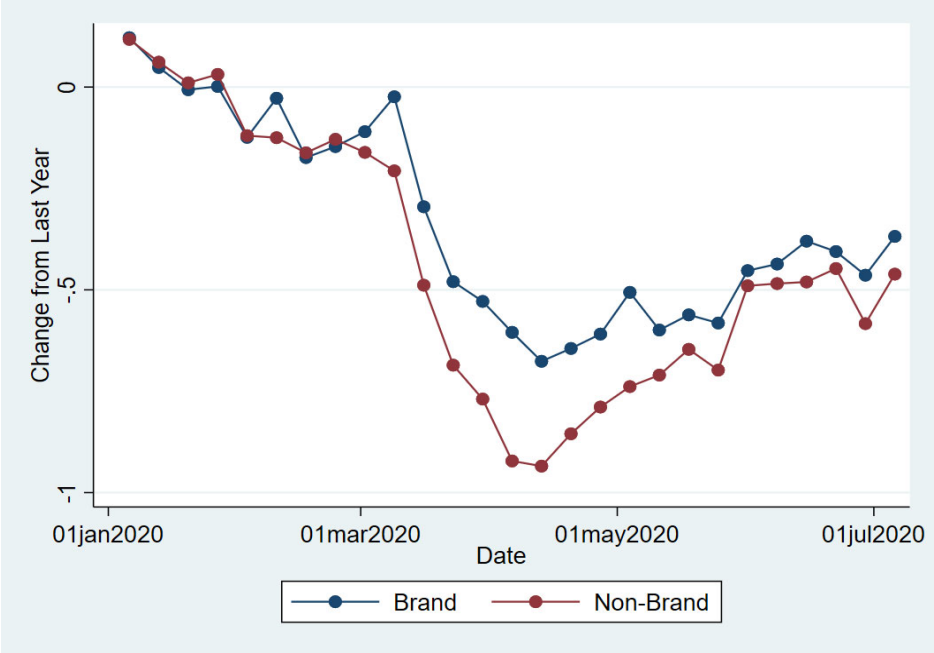
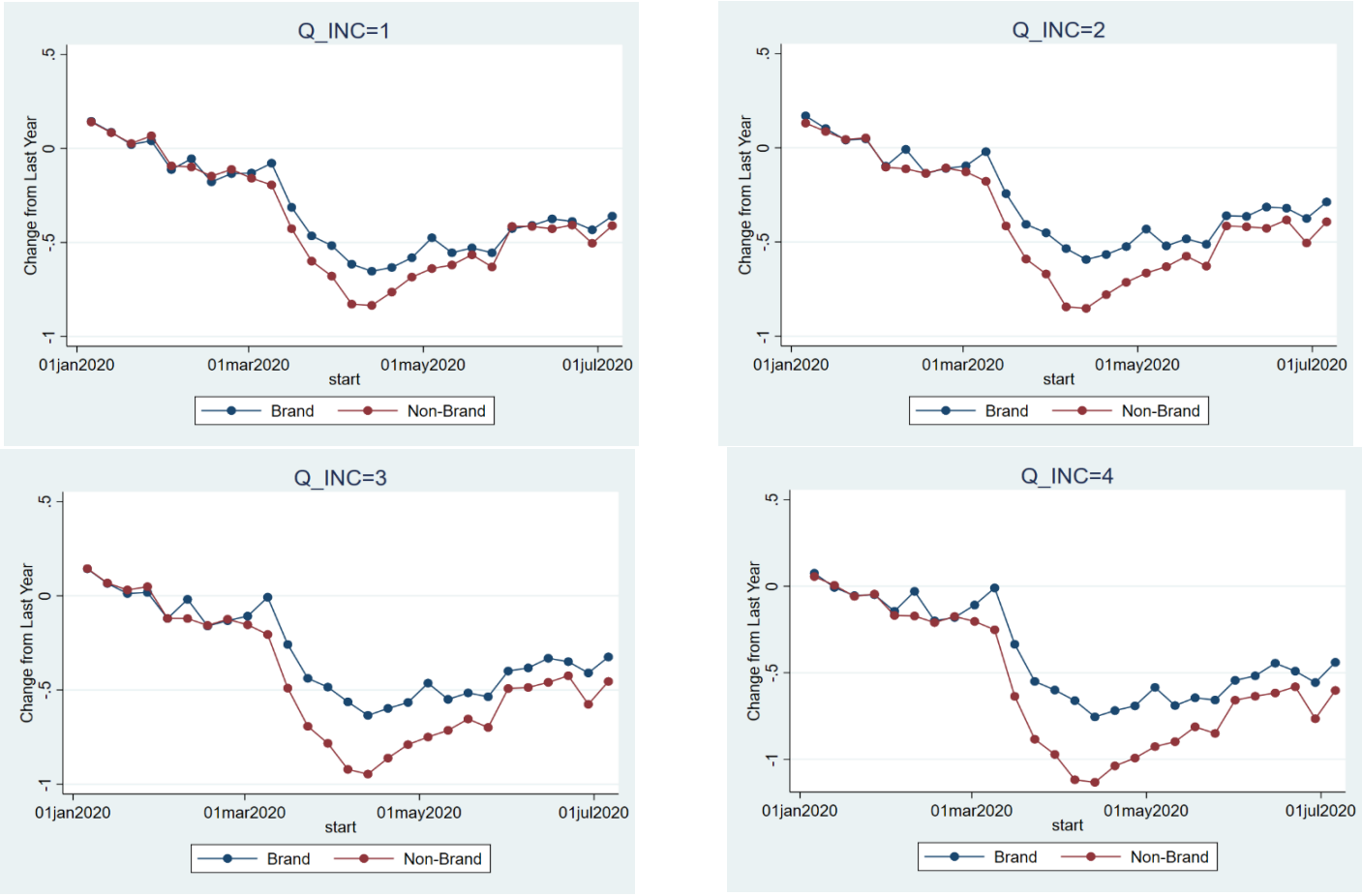


Figure 3: Change in Foot Traffic Over Time - Cross-Sectional

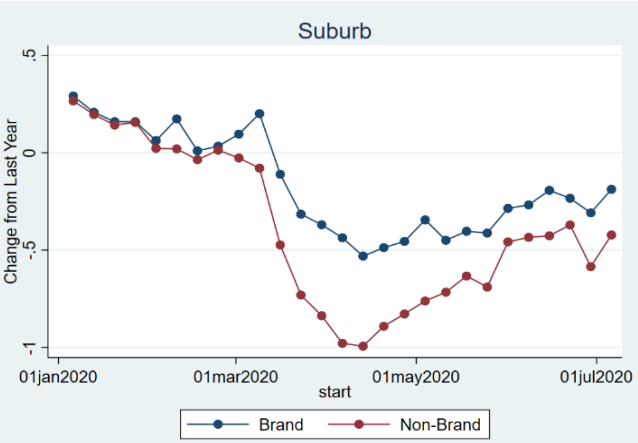
This figures shows the average change in number of visits over our sample period for brand stores and independent stores. Panel A presents the changes by income quartile. Panel B presents the changes for different locations. We define a zipcode as urban, suburb, second city, or town and rural areas if the percentage of households in the category is greater than 50%. Panel C presents the estimated coefficients for business and non-business districts. We define business districts as zip codes with a business-residential ratio greater than two.

Panel A

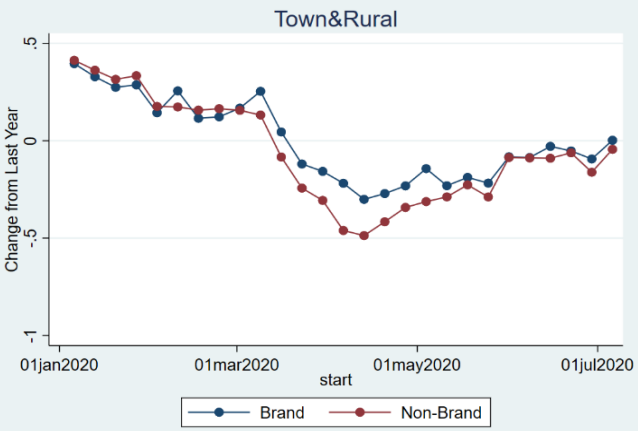


Panel B

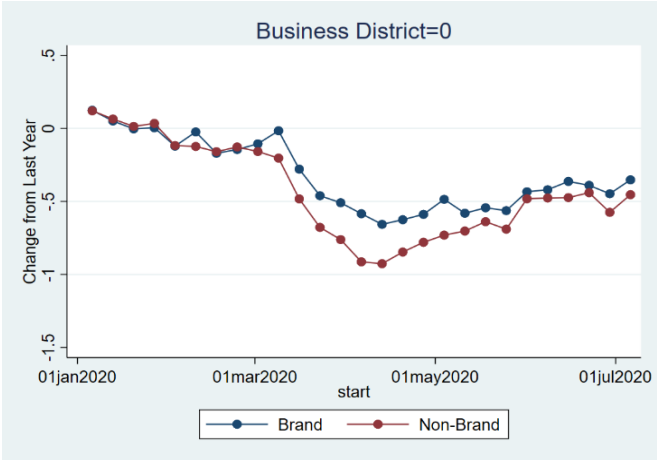

Urban
Change from Last Year
-1
-.5
0
.5
01jan2020
01mar2020
01may2020
01jul2020
start
Brand
Non-Brand


Suburb
Change from Last Year
-1
-.5
0
.5
01jan2020
01mar2020
01may2020
01jul2020
start
Brand
Non-Brand

2ndCity
Change from Last Year
-1
-.5
0
.5
01jan2020
01mar2020
01may2020
01jul2020
start
Brand
Non-Brand


Town&Rural
Change from Last Year
-1
-.5
0
.5
01jan2020
01mar2020
01may2020
01jul2020
start
Brand
Non-Brand

Panel C


Business District=0
Change from Last Year
.5
0
-.5
-1
-1.5
01jan2020
01mar2020
01may2020
01jul2020
start
Brand
Non-Brand

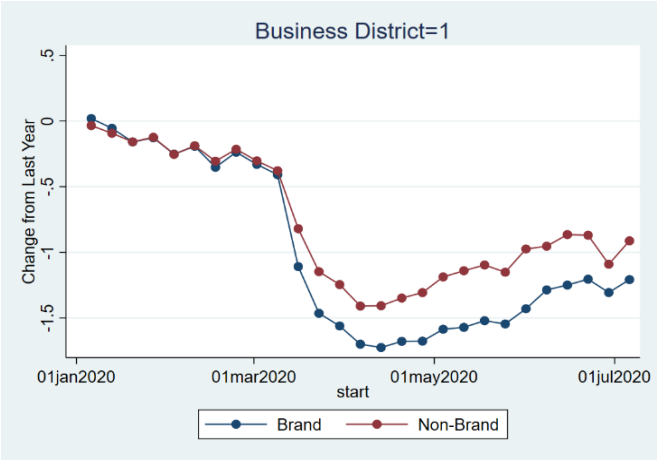

Business District=1
Change from Last Year
.5
0
-.5
-1
-1.5
01jan2020
01mar2020
01may2020
01jul2020
start
Brand
Non-Brand

Figure 4 Change of Visits and Distance by the Business-Residential Ratio

This figures shows the estimated coefficients and CI for the interaction term between the indicator for stay-at-home period (SAH) and the indicator for groups using the business-residential ratio. The cutoff for the six groups are 0.25, 0.5, 0.75, 1, and 2. We run regressions using specifications in Table 2 Column 2 for the top panel, and Table 2 column x for the bottom panel.

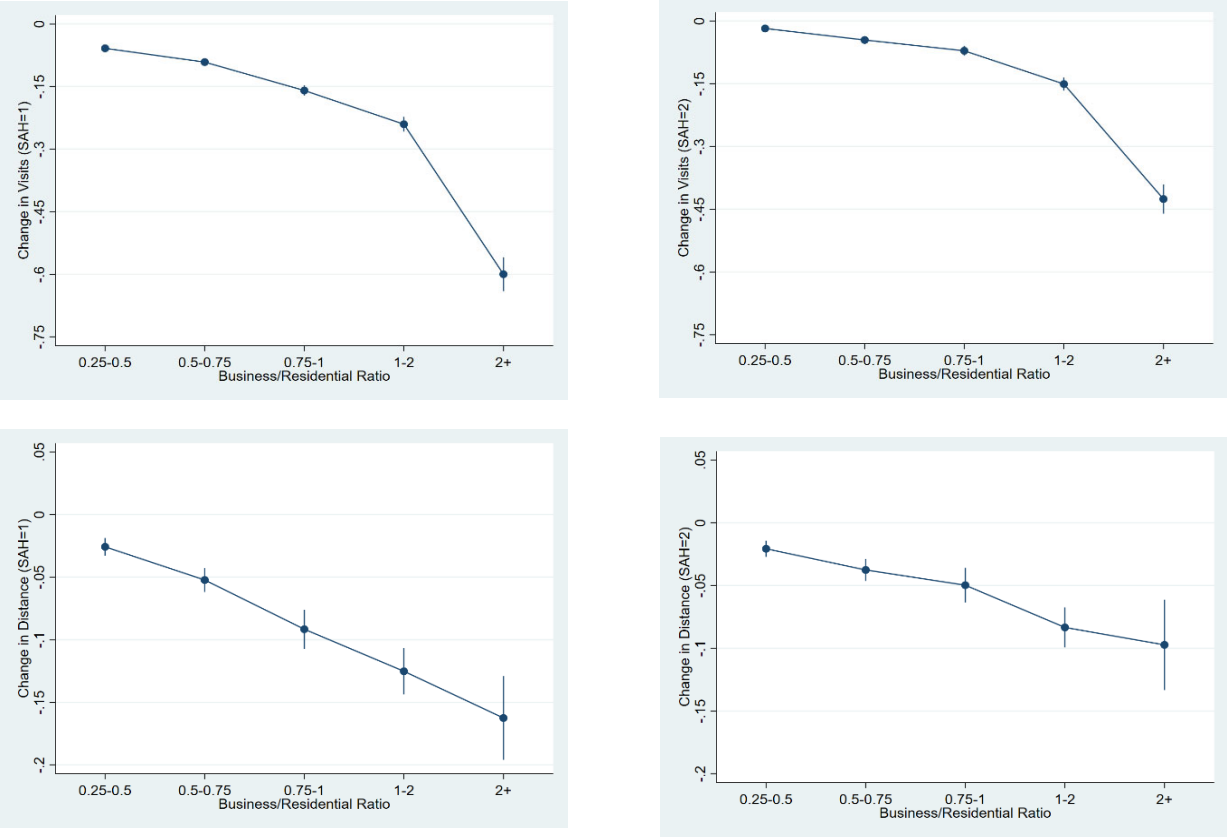
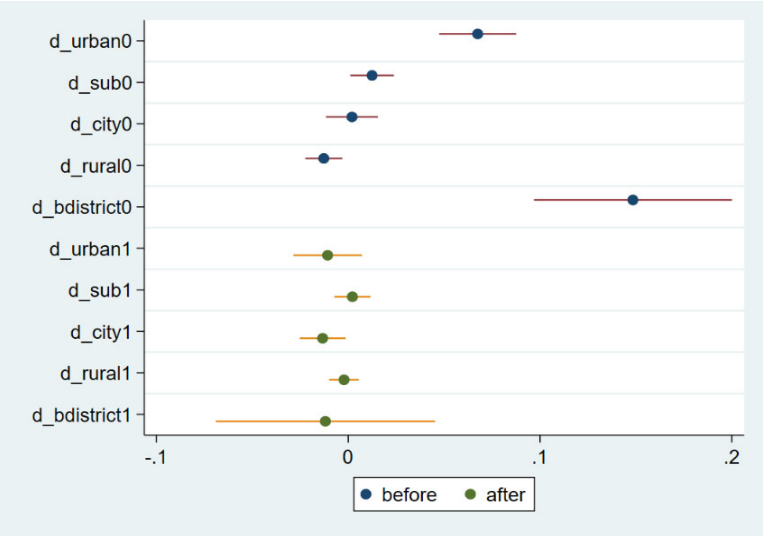


Figure 5: Median Distance for Shoppers - Before and After

This figure shows the estimated coefficients (with 95% confidence interval) for location indicators (Panel A) and business residential ratio groups (Panel B) before and after the COVID-pandemic. For each panel, we regress the log of distance on interactions between the location or group indicators and the time indicator for the stay-at-home period (SAH). d_indicator0 is the estimated coefficient for (SAH=0) x d_indicator and d_indicator1 is the estimated coefficient for (SAH=1) x d_indicator. In both regressions, we include the store fixed effect and cluster errors by county. The cutoff points for the business-residential ratio for the six groups are 0.25, 0.5, 0.75, 1, and 2.

Panel A: By Locations



Panel B: By Business/Residerntial Ratio

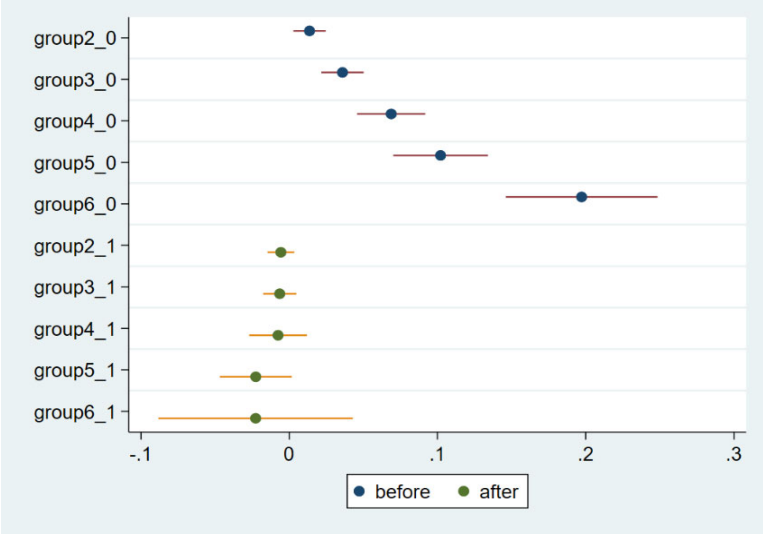


Table 1: Summary Statistitics

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	9,716	13,288	11,894
# of Visits (Jan 2020)	244	511	407
% of Urban	0.190	0.184	0.186
% of Suburb	0.173	0.279	0.238
% of 2ndCity	0.146	0.201	0.179
% of Town & Rural	0.491	0.336	0.397
D_BDistrict	0.017	0.020	0.019
D_LowInc	0.294	0.178	0.223
D_HighInc	0.251	0.391	0.337
Median Household Income	68,775	78,191	74,516
# of Banks	7.37	8.56	8.10
Exp_SBL	0.76	0.83	0.80
# of Obs	12,565	19,630	32,195

Panel B

State	Frequency	Percent	State	Frequency	Percent
AK	22	0.07	MS	370	1.15
AL	733	2.28	MT	91	0.28
AR	405	1.26	NC	1,135	3.53
AZ	459	1.43	ND	71	0.22
CA	3,190	9.91	NE	202	0.63
CO	261	0.81	NH	155	0.48
CT	375	1.16	NJ	1,148	3.57
DC	85	0.26	NM	132	0.41
DE	131	0.41	NV	210	0.65
FL	2,250	6.99	NY	2,459	7.64
GA	1,051	3.26	OH	1,183	3.67
HI	90	0.28	OK	433	1.34
IA	322	1.00	OR	235	0.73
ID	107	0.33	PA	1,618	5.03
IL	1,133	3.52	RI	127	0.39
IN	634	1.97	SC	570	1.77
KS	334	1.04	SD	83	0.26
KY	615	1.91	TN	731	2.27
LA	637	1.98	TX	2,392	7.43
MA	698	2.17	UT	154	0.48
MD	558	1.73	VA	738	2.29
ME	177	0.55	VT	97	0.30
MI	1,239	3.85	WA	513	1.59
MN	406	1.26	WI	472	1.47
MO	650	2.02	WV	280	0.87
			WY	34	0.11
Total				**32,195**	**100.00**

Table 2: Changes 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				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
SAH =1	-0.622***					-0.122***				
	(0.011)					(0.004)				
SAH =2	-0.391***					-0.008***				
	(0.012)					(0.002)				
(SAH = 1) x D_BDistrict		-0.536***			-0.528***		-0.131***			-0.128***
		(0.066)			(0.019)		(0.028)			(0.017)
(SAH = 2) x D_BDistrict		-0.395***			-0.386***		-0.075***			-0.075***
		(0.050)			(0.017)		(0.027)			(0.018)
(SAH = 1) x D_Urban			-0.140***		-0.128***			-0.051***		-0.047***
			(0.007)		(0.007)			(0.007)		(0.008)
(SAH = 2) x D_Urban			-0.107***		-0.096***			-0.012*		-0.012**
			(0.007)		(0.007)			(0.006)		(0.006)
(SAH = 1) x D_Suburb			-0.071***		-0.056***			-0.012**		-0.010*
			(0.005)		(0.005)			(0.006)		(0.006)
(SAH = 2) x D_Suburb			-0.020***		-0.010**			-0.003		0.001
			(0.005)		(0.005)			(0.005)		(0.005)
(SAH = 1) x D_2ndCity			-0.044***		-0.055***			-0.007		-0.007
			(0.006)		(0.006)			(0.006)		(0.007)
(SAH = 2) x D_2ndCity			-0.035***		-0.039***			-0.008		-0.013**
			(0.005)		(0.005)			(0.005)		(0.006)
(SAH = 1) x D_Town			0.005		0.011**			0.006		0.006
			(0.005)		(0.005)			(0.006)		(0.006)
(SAH = 2) x D_Town			0.004		0.008*			-0.005		-0.002
			(0.004)		(0.004)			(0.005)		(0.005)
(SAH = 1) x D_LowInc				-0.022	-0.001				-0.007	-0.001
				(0.015)	(0.005)				(0.011)	(0.006)
(SAH = 2) x D_LowInc				-0.029***	-0.009**				-0.002	0.002
				(0.011)	(0.004)				(0.007)	(0.005)
(SAH = 1) x D_HighInc				-0.030*	-0.040***				0.003	-0.002
				(0.016)	(0.005)				(0.009)	(0.005)
(SAH = 2) x D_HighInc				-0.012	-0.028***				-0.010*	-0.013***
				(0.010)	(0.004)				(0.006)	(0.004)
Constant	0.108***	-0.147***	-0.132***	-0.145***	-0.124***	-0.061***	-0.088***	-0.084***	-0.088***	-0.083***
	(0.006)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.000)	(0.002)	(0.002)	(0.002)
Observations	794,855	780,403	779,701	780,403	779,701	738,520	723,664	723,120	723,664	723,120
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	0.525	0.589	0.587	0.586	0.590	0.219	0.268	0.268	0.268	0.268

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) or median distance of visitors (Panel B) 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_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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DEP VAR = Change in the # of Visits							
D_Brand	0.076***						
	(0.003)						
(SAH=1) x D_Brand	0.259***	0.259***	0.265***	0.273***	0.240***	0.273***	0.274***
	(0.007)	(0.005)	(0.005)	(0.006)	(0.005)	(0.010)	(0.011)
(SAH=2) x D_Brand	0.086***	0.092***	0.095***	0.097***	0.088***	0.109***	0.110***
	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.009)	(0.009)
(SAH=1) x D_Brand x D_BDistrict			-0.357***				-0.338***
			(0.032)				(0.033)
(SAH=2) x D_Brand x D_BDistrict			-0.209***				-0.192***
			(0.027)				(0.027)
(SAH=1) x D_Brand x D_LowInc				-0.064***			-0.036***
				(0.008)			(0.009)
(SAH=2) x D_Brand x D_LowInc				-0.020***			-0.017**
				(0.007)			(0.008)
(SAH=1) x D_Brand x D_HighInc					0.055***		0.018*
					(0.008)		(0.010)
(SAH=2) x D_Brand x D_HighInc					0.010		0.003
					(0.008)		(0.009)
(SAH=1) x D_Brand x D_Urban						-0.056***	-0.034**
						(0.015)	(0.015)
(SAH=2) x D_Brand x D_Urban						-0.047***	-0.035**
						(0.015)	(0.015)
(SAH=1) x D_Brand x D_Suburb						0.061***	0.052***
						(0.014)	(0.015)
(SAH=2) x D_Brand x D_Suburb						0.003	0.003
						(0.012)	(0.013)
(SAH=1) x D_Brand x D_2ndCity						-0.004	0.015
						(0.015)	(0.015)
(SAH=2) x D_Brand x D_2ndCity						0.021*	0.029**
						(0.013)	(0.013)
(SAH=1) x D_Brand x D_Town						-0.043***	-0.038***
						(0.012)	(0.012)
(SAH=2) x D_Brand x D_Town						-0.031***	-0.028***
						(0.010)	(0.011)
Constant	-0.267***	-0.219***	-0.219***	-0.220***	-0.220***	-0.221***	-0.221***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	677,858	677,858	677,858	677,858	677,858	677,603	677,603
Store FE	No	Yes	Yes	Yes	Yes	Yes	Yes
ZIP-Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.380	0.600	0.600	0.600	0.600	0.600	0.600

Panel B

DEP VAR = Change in Median Distance	(1)	(2)	(3)	(4)	(5)	(6)	(7)
D_Brand	-0.043***						
	(0.002)						
(SAH=1) x D_Brand	-0.060***	-0.065***	-0.062***	-0.061***	-0.054***	-0.067***	-0.051***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.011)	(0.012)
(SAH=2) x D_Brand	-0.057***	-0.054***	-0.052***	-0.050***	-0.055***	-0.043***	-0.041***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.010)	(0.010)
(SAH=1) x D_Brand x D_BDistrict			-0.148***				-0.132***
			(0.041)				(0.041)
(SAH=2) x D_Brand x D_BDistrict			-0.096***				-0.070**
			(0.033)				(0.033)
(SAH=1) x D_Brand x D_LowInc				-0.014			-0.031***
				(0.010)			(0.011)
(SAH=2) x D_Brand x D_LowInc				-0.015**			-0.012
				(0.008)			(0.009)
(SAH=1) x D_Brand x D_HighInc					-0.036***		-0.049***
					(0.009)		(0.012)
(SAH=2) x D_Brand x D_HighInc					0.004		-0.001
					(0.007)		(0.009)
(SAH=1) x D_Brand x D_Urban						-0.005	0.005
						(0.016)	(0.016)
(SAH=2) x D_Brand x D_Urban						-0.052***	-0.047***
						(0.013)	(0.013)
(SAH=1) x D_Brand x D_Suburb						-0.016	0.009
						(0.015)	(0.016)
(SAH=2) x D_Brand x D_Suburb						-0.009	-0.008
						(0.012)	(0.013)
(SAH=1) x D_Brand x D_2ndCity						-0.019	-0.019
						(0.016)	(0.017)
(SAH=2) x D_Brand x D_2ndCity						-0.029**	-0.024*
						(0.013)	(0.014)
(SAH=1) x D_Brand x D_Town						0.031**	0.035**
						(0.014)	(0.014)
(SAH=2) x D_Brand x D_Town						0.018	0.020*
						(0.011)	(0.011)
Constant	-0.032***	-0.060***	-0.060***	-0.061***	-0.060***	-0.060***	-0.060***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	621,528	621,325	621,325	621,325	621,325	621,181	621,181
Store FE	No	Yes	Yes	Yes	Yes	Yes	Yes
County-Week	No	No	No	No	No	No	No
ZIP-Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.118	0.269	0.269	0.269	0.269	0.269	0.269

Table 4: The Impact of PPP Loans

This table reports regression results to examine the impact of PPP loans between 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. 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 indicator variables for PPP and PPP_Total for Panel A, and the log of the loan amount for Panel B. 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: Indicator Variables						Panel B: Continuous Variables					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
D_Brand	0.079***	0.078***	0.078***				0.079***	0.079***	0.079***			
	(0.003)	(0.003)	(0.003)				(0.003)	(0.003)	(0.003)			
(SAH=1) x D_Brand	0.256***	0.253***	0.250***	0.263***	0.278***	0.277***	0.256***	0.262***	0.257***	0.264***	0.288***	0.287***
	(0.007)	(0.011)	(0.011)	(0.005)	(0.009)	(0.009)	(0.007)	(0.010)	(0.011)	(0.005)	(0.009)	(0.009)
(SAH=2) x D_Brand	0.096***	0.085***	0.090***	0.101***	0.115***	0.117***	0.098***	0.096***	0.099***	0.103***	0.129***	0.130***
	(0.005)	(0.011)	(0.011)	(0.006)	(0.010)	(0.010)	(0.005)	(0.011)	(0.011)	(0.006)	(0.010)	(0.010)
PPP	0.043***		0.044***				0.004***		0.004***			
	(0.005)		(0.005)				(0.000)		(0.000)			
D_Brand x PPP	-0.028***		-0.030***	-0.015***		-0.011**	-0.002***		-0.002***	-0.001***		-0.001*
	(0.005)		(0.005)	(0.005)		(0.006)	(0.000)		(0.000)	(0.000)		(0.000)
PPP_total		0.011	0.004					-0.000	-0.001			
		(0.014)	(0.014)					(0.001)	(0.001)			
D_Brand x PPP_total		-0.007	0.007		-0.023***	-0.018**		-0.001*	-0.000		-0.002***	-0.002***
		(0.010)	(0.011)		(0.008)	(0.009)		(0.001)	(0.001)		(0.000)	(0.001)
Ln_estab	-0.052***	-0.052***	-0.052***				-0.052***	-0.052***	-0.052***			
	(0.002)	(0.002)	(0.002)				(0.002)	(0.002)	(0.002)			
(SAH=1) x Ln_estab	-0.181***	-0.180***	-0.182***				-0.182***	-0.178***	-0.180***			
	(0.008)	(0.008)	(0.008)				(0.008)	(0.008)	(0.008)			
(SAH=2) x Ln_estab	-0.101***	-0.097***	-0.101***				-0.102***	-0.096***	-0.101***			
	(0.005)	(0.005)	(0.005)				(0.005)	(0.005)	(0.005)			
Ln_household	0.042***	0.042***	0.042***				0.042***	0.042***	0.042***			
	(0.003)	(0.003)	(0.003)				(0.003)	(0.003)	(0.003)			
(SAH =1) x Ln_household	0.161***	0.161***	0.161***				0.161***	0.161***	0.161***			
	(0.008)	(0.008)	(0.008)				(0.008)	(0.008)	(0.008)			
(SAH =2) x Ln_household	0.099***	0.099***	0.099***				0.099***	0.099***	0.099***			
	(0.006)	(0.006)	(0.006)				(0.006)	(0.006)	(0.006)			
Constant	-0.466***	-0.474***	-0.468***	-0.220***	-0.219***	-0.220***	-0.465***	-0.471***	-0.462***	-0.220***	-0.219***	-0.219***
	(0.013)	(0.014)	(0.014)	(0.001)	(0.001)	(0.001)	(0.013)	(0.014)	(0.014)	(0.001)	(0.001)	(0.001)
Observations	780,403	780,403	780,403	677,858	677,858	677,858	780,403	780,403	780,403	677,858	677,858	677,858
Store FE	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
County-Week FE	Yes	Yes	Yes				Yes	Yes	Yes			
ZIP-Week FE	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Adjusted R-squared	0.348	0.348	0.348	0.600	0.600	0.600	0.348	0.348	0.348	0.600	0.600	0.600

Table 5: The Impact of PPP Loans - Cross-Sectional Analysis

This table reports regression results to examine the impact of PPP loans by income levels (Panel A), locations (Panel B), and business districts (Panel C). The dependent variable is the change in the number of visits from the same month last year. Panel A presents the estimated coefficients by income quartile. Panel B presents the estimated coefficients for different locations. We define a zipcode as urban, suburb, second city, or town and rural areas if the percentage of households in the category is greater than 50%. Panel C presents the estimated coefficients for business and non-business districts. We define business districts as zip codes with a business-residential ratio greater than two. 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 is an indicator variable that equals one if the zipcode has any approved PPP loans in the naics code of 446110 by the beginning of the week. 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: Income Levels				Panel B: Locations				Panel C: Business Districts	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	Q = 1	Q = 2	Q = 3	Q = 4	Urban	Suburb	2ndCity	Town	Business District	Non-Business District
(SAH=1) x D_Brand	0.207***	0.236***	0.284***	0.304***	0.226***	0.342***	0.270***	0.221***	0.270***	-0.089**
	(0.008)	(0.008)	(0.009)	(0.009)	(0.012)	(0.010)	(0.012)	(0.007)	(0.005)	(0.035)
(SAH=2) x D_Brand	0.072***	0.106***	0.098***	0.119***	0.085***	0.129***	0.132***	0.063***	0.105***	-0.107***
	(0.010)	(0.009)	(0.010)	(0.010)	(0.013)	(0.011)	(0.013)	(0.008)	(0.006)	(0.038)
D_Brand x PPP	0.007	-0.014	-0.007	-0.035***	-0.035***	-0.029***	-0.004	0.022***	-0.016***	-0.010
	(0.009)	(0.009)	(0.010)	(0.010)	(0.012)	(0.011)	(0.013)	(0.008)	(0.005)	(0.041)
Constant	-0.179***	-0.161***	-0.199***	-0.302***	-0.436***	-0.291***	-0.212***	-0.052***	-0.212***	-0.655***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.009)
Observations	148,872	152,185	144,613	232,188	145,199	151,030	82,157	212,785	665,605	12,253
Store FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
ZIP-Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.591	0.583	0.580	0.621	0.640	0.599	0.562	0.515	0.588	0.744

Table 6: The Impact of PPP Loans - IV Estimates

This table reports the results from IV regressions of changes in the number of visits on measures of PPP loans. The endogeous variable is PPP, the log of PPP loan amount for the industry in the zip code. We use three instrument variables. PPP_Exp is computed as the average of the PPP lending fo each bank with a branch presence in the zip code. Topbanks_1to4 (Topbanks_5to10) is an indicator that equals 1 if there is a bank brach from the top 4 (top 5 to 10) banks in the zip code. 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. 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. We include store fixed effects and (county x week) fixed effects. Standard errors clustered by county x week are reported in parentheses. *, **, *** represent significance at 10%, 5%, and 1%, respectively.

	Second-Stage	First Stage	
DEP VAR	Change in # of Visits	PPP	D_Brand x PPP
PPP	0.110***		
	(3.51)		
D_Brand x PPP	-0.103***		
	(-2.84)		
PPP_Exp		-0.00513	0.00498*
		(-1.37)	(1.90)
Topbank_1to4		0.0587**	0.0259
		(2.16)	(1.31)
Topbank_5to10		0.217***	0.164***
		(8.37)	(9.03)
D_Brand	0.123***	-0.0423***	0.405***
	(7.55)	(-8.46)	(23.39)
(SAH=1) x D_Brand	0.581***	-0.900***	2.254***
	(5.39)	(-26.74)	(29.17)
(SAH=2) x D_Brand	0.860***	-1.601***	5.866***
	(3.30)	(-57.60)	(67.03)
Ln_estab	-0.0610***	0.0617***	0.00734
	(-23.24)	(4.74)	(0.81)
(SAH=1) x Ln_estab	-0.226***	1.025***	0.662***
	(-14.32)	(17.19)	(17.98)
(SAH=2) x Ln_estab	-0.198***	2.171***	1.362***
	(-7.00)	(35.30)	(29.34)
Ln_household	0.0369***	0.0853***	0.0321***
	(11.15)	(9.27)	(5.06)
(SAH =1) x Ln_household	0.160***	0.0570	0.0174
	(19.60)	(0.86)	(0.40)
(SAH =2) x Ln_household	0.0969***	-0.0761	-0.123*
	(15.29)	(-0.93)	(-1.95)
N	762407		
Store FE	No		
County-Week FE	Yes		
Kleibergen-Paap F Statistic	17.3		

Table 7: The Effect of Small Business Lending

This table reports regression results to examine the effect of small business lending 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. 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. D_Banks is an indicator variable that equals one if the number of bank branches in the zip code is in the top quartile in our sample 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.

VARIABLES	(1)	(2)	(3)	(4)
D_Brand	0.085***	0.084***		
	(0.003)	(0.004)		
(SAH=1) x D_Brand	0.258***	0.275***	0.272***	0.271***
	(0.007)	(0.008)	(0.006)	(0.006)
(SAH=2) x D_Brand	0.078***	0.087***	0.092***	0.091***
	(0.006)	(0.007)	(0.006)	(0.006)
D_SBL	0.023***			
	(0.004)			
(SAH=1) x D_SBL	0.030***			
	(0.008)			
(SAH=2) x D_SBL	0.009			
	(0.007)			
D_SBL x D_Brand	-0.020***	-0.019***		
	(0.004)	(0.005)		
(SAH=1) x D_SBL x D_Brand	-0.033***	-0.043***	-0.034***	-0.036***
	(0.010)	(0.010)	(0.008)	(0.009)
(SAH=2) x D_SBL x D_Brand	0.001	-0.001	0.000	-0.002
	(0.007)	(0.009)	(0.007)	(0.008)
(SAH=1) x D_Banks x D_Brand				0.003
				(0.009)
(SAH=2) x D_Banks x D_Brand				0.004
				(0.007)
Ln_estab	-0.056***			
	(0.002)			
(SAH=1) x Ln_estab	-0.182***			
	(0.008)			
(SAH=2) x Ln_estab	-0.100***			
	(0.006)			
Ln_household	0.042***			
	(0.003)			
(SAH =1) x Ln_household	0.162***			
	(0.008)			
(SAH =2) x Ln_household	0.100***			
	(0.006)			
Constant	-0.446***	-0.267***	-0.220***	-0.220***
	(0.013)	(0.001)	(0.001)	(0.001)
Observations	780,403	677,858	677,858	677,858
Store FE	No	No	Yes	Yes
COUNTY-Week FE	Yes	No	No	No
ZIP-Week FE	No	Yes	Yes	Yes
Adjusted R-squared	0.348	0.380	0.600	0.600

Table 8: The Effect of Small Business Lending - Cross-Sectional Analysis

This table reports regression results to examine the effect of small business lending by income levels (Panel A), locations (Panel B), and business districts (Panel C). The dependent variable is the change in the number of visits from the same month last year. Panel A presents the estimated coefficients by income quartile. Panel B presents the estimated coefficients for different locations. We define a zipcode as urban, suburb, second city, or town and rural areas if the percentage of households in the category is greater than 50%. Panel C presents the estimated coefficients for business and non-business districts. We define business districts as zip codes with a business-residential ratio greater than two. 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. PD_SBL is an indicator variable the equals one if the measure of small business lending exposure 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: Income Levels				Panel B: Locations				Panel C: Business Districts	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	Q = 1	Q = 2	Q = 3	Q = 4	Urban	Suburb	2ndCity	Town	Business District	Non-Business District
(SAH=1) x D_Brand	0.232***	0.261***	0.302***	0.288***	0.251***	0.317***	0.273***	0.236***	0.273***	0.147***
	(0.010)	(0.010)	(0.011)	(0.010)	(0.013)	(0.012)	(0.013)	(0.009)	(0.006)	(0.052)
(SAH=2) x D_Brand	0.078***	0.096***	0.101***	0.094***	0.062***	0.104***	0.130***	0.068***	0.092***	0.069
	(0.009)	(0.009)	(0.010)	(0.009)	(0.013)	(0.011)	(0.011)	(0.008)	(0.006)	(0.044)
(SAH=1) x D_SBL x D_Brand	-0.064***	-0.064***	-0.052***	0.018	-0.101***	0.045**	-0.013	-0.019	-0.021***	-0.373***
	(0.015)	(0.014)	(0.016)	(0.015)	(0.016)	(0.018)	(0.021)	(0.013)	(0.008)	(0.062)
(SAH=2) x D_SBL x D_Brand	-0.003	0.004	-0.020	0.012	0.003	0.020	-0.000	0.021**	0.009	-0.297***
	(0.012)	(0.013)	(0.014)	(0.013)	(0.017)	(0.016)	(0.017)	(0.010)	(0.007)	(0.055)
Constant	-0.179***	-0.161***	-0.199***	-0.300***	-0.435***	-0.290***	-0.212***	-0.052***	-0.211***	-0.656***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.008)
Observations	148,872	152,185	144,613	232,188	145,199	151,030	82,157	212,785	665,605	12,253
Store FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
ZIP-Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.591	0.583	0.580	0.621	0.640	0.599	0.562	0.515	0.588	0.745

Table 9: Brand vs. Independent Stores - The Size Effect

This table reports regression results to examine the differential between 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. D_Large is an indicator variable that equals one if the store is in the top quartile by square footage. 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.

VARIABLES	(1)	(2)	(3)
D_Brand	0.071***	0.075***	
	(0.003)	(0.003)	
(SAH=1) x D_Brand	0.217***	0.235***	0.232***
	(0.007)	(0.007)	(0.005)
(SAH=2) x D_Brand	0.060***	0.070***	0.077***
	(0.005)	(0.005)	(0.004)
D_Large	-0.019***	-0.008**	
	(0.004)	(0.004)	
(SAH=1) x D_Large	-0.061***	-0.055***	-0.067***
	(0.009)	(0.010)	(0.007)
(SAH=1) x D_Large	-0.051***	-0.056***	-0.050***
	(0.007)	(0.008)	(0.007)
D_Brand x D_Large	0.022***	0.008	
	(0.004)	(0.005)	
(SAH =1) x D_Brand x D_Large	0.120***	0.102***	0.113***
	(0.011)	(0.012)	(0.009)
(SAH =2) x D_Brand x D_Large	0.085***	0.072***	0.064***
	(0.009)	(0.010)	(0.008)
Constant	-0.241***	-0.259***	-0.213***
	(0.002)	(0.002)	(0.001)
Observations	780,403	677,858	677,858
Store FE	No	No	Yes
CTY-Week FE	Yes	No	No
ZIP-Week FE	No	Yes	Yes
Adjusted R-squared	0.335	0.381	0.600

Table 10: Brand vs. Independent Stores - Consumer Preference

This table reports regression results to examine the effect of 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 uses consumers' preferences for local stores. 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. Panel B uses experience for shopping at Amazon.com. 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: Preference for Local Stores (D_Local)			Panel B: Shopping at Amazon.com (D_AMZ)		
VARIABLES	(1)	(2)	(3)	(1)	(2)	(3)
D_Brand	0.073***	0.073***		0.078***	0.079***	
	(0.003)	(0.003)		(0.003)	(0.003)	
(SAH=1) x D_Brand	0.260***	0.273***	0.272***	0.244***	0.256***	0.252***
	(0.007)	(0.007)	(0.005)	(0.007)	(0.007)	(0.006)
(SAH=2) x D_Brand	0.092***	0.095***	0.100***	0.081***	0.086***	0.091***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)
D_Consumer	-0.031***			-0.000		
	(0.004)			(0.005)		
(SAH=1) x D_Consumer	0.046***			-0.078***		
	(0.008)			(0.010)		
(SAH=2) x D_Consumer	0.037***			-0.031***		
	(0.007)			(0.009)		
D_Brand x D_Consumer	0.011***	0.014***		-0.007	-0.010	
	(0.004)	(0.005)		(0.005)	(0.006)	
(SAH=1) x D_Consumer x D_Brand	-0.064***	-0.055***	-0.057***	0.013	0.016	0.029***
	(0.010)	(0.011)	(0.009)	(0.011)	(0.014)	(0.010)
(SAH=2) x D_Consumer x D_Brand	-0.049***	-0.039***	-0.038***	0.003	-0.000	0.003
	(0.009)	(0.010)	(0.008)	(0.010)	(0.012)	(0.010)
Constant	-0.249***	-0.267***	-0.220***	-0.244***	-0.267***	-0.220***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Observations	780,403	677,858	677,858	780,403	677,858	677,858
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	0.334	0.380	0.600	0.335	0.380	0.600