Measuring local consumption with payment cards and cell phone pings*

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Abstract

We compare two widely used sources of consumption data: payment card transactions (from credit and debit cards) and cell phone location pings. We find they are positively but imperfectly correlated; payment card usage is higher among higher-income consumers, while cell phone pings only loosely track consumer spending. We develop a methodology that combines both sources to measure local retail spending and show that it closely tracks more aggregated government data. We illustrate its use by quantifying local fiscal multipliers. We show that the impacts of government spending shocks are highly localized, decay spatially, and are heterogeneous across store categories.

Keywords: retail spending, foot traffic, location data, payment cards, fiscal multipliers

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1 Introduction

Many government policy interventions impact economic activity heterogeneously across granular geographic areas, such as zip codes, neighborhoods, or Census tracts. Examples of this at the national level include fiscal and monetary policy, which may have heterogeneous effects across households (Kaplan et al., 2018; Kaplan and Violante, 2018; Brinca et al., 2016), and federal place-based policies that target Census tracts or zip codes to receive investment or employment subsidies (Busso et al., 2013; Neumark and Young, 2019; Corinth and Feldman, 2024). Examples at the local and state level include zoning and land use restrictions, housing market regulations, and labor market policies, all of which impact granular geographic areas. However, many core government datasets (including GDP, local employment, and spending) are only available at higher levels of aggregation, such as city, county, or even state. This lack of granular economic data limits the ability of policymakers and researchers to examine the local effects of these policies using traditional data sources.

In recent years, researchers have leveraged new data that offer a more granular view of economic activity, including foot traffic data collected from cell phone pings and consumer spending measured from credit and debit card transactions.[1] While these data sources are available at higher frequency and lower levels of aggregation than government data, they are imperfect proxies for total consumption. Cell phone location data measures the movement patterns of consumers but not their spending. Expenditures from credit and debit card purchases may suffer from selection across both consumers and stores.

In this paper, we compare two examples of these widely used data sources; we use foot traffic data provided by Safegraph and credit and debit card expenditures from a major US payment card network. We show that while the two sources largely capture similar patterns of local economic activity across zip codes and store categories, each source on its own has important limitations. Visits from foot traffic data only loosely track actual

[1] Foot traffic data has been used by Chen and Rohla (2018); Athey et al. (2018); Allcott et al. (2020); Chen and Pope (2020); Chiou and Tucker (2020); Almagro et al. (2020); Engle et al. (2020); Painter and Qiu (2020); Brzezinski et al. (2020); Chen et al. (2021); Glaeser et al. (2022); Athey et al. (2021); Couture et al. (2019, 2022); Chen et al. (2022); Fe and Sanfelice (2022); Duranton and Handbury (2023); Kreindler and Miyauchi (2023); Narang and Luco (2024), among many others. Similar credit card data has been used by Diamond et al. (2021); Ganong and Noel (2019, 2020); Einav et al. (2021); Klopack (2022); Relihan (2022); Dolfen et al. (2023); Conway and Boxell (2023); Einav et al. (2023); Duguid et al. (2023), among others.

expenditures, which are the outcome of interest for many studies of consumption. This is a particular challenge for researchers who seek to proxy for aggregate consumption due to significant variation in spending per visit across different store categories. The payment card data overcomes this limitation by directly measuring spending. However, payment card data is not widely accessible to researchers. Payment cards also tend to be more heavily used by higher-income consumers. Thus, using an unadjusted measure of card spending may underrepresent the activity of lower-income groups.

We then combine both data sets to create a measure of zip code-level retail expenditures by store category that overcomes these limitations. We first scale up the observed expenditure in the payment card data to be representative of overall retail consumption. To address selection into which consumers hold payment cards, we incorporate data from the Diary of Consumer Payment Choice, which records payment instrument use across US households, along with their demographic information. Next, we compute the ratio of total expenditure to foot traffic visits for each zip code by store category. The output of this exercise is a set of weights that can be applied to the foot traffic data to recover spending, which we hope will be useful to other researchers with similar data. We validate our estimated spending measure by showing that, after aggregating it at the county and state level, it is highly correlated with retail sales data available from government sources.[2]

To illustrate the use of these weights, we use the transformed data to address a long-standing question in economics: what is the effect of government spending on (localized) consumer spending? The measurement of fiscal multipliers has been extensively studied using data at the state and county level (Nakamura and Steinsson, 2014, for example), with the most geographically granular application being at the city or MSA level (Auerbach et al., 2020). We perform a similar analysis at the zip code level to examine how Department of Defense (DOD) expenditure in a given zip code impacts nearby consumer retail spending.

The empirical exercise yields several novel findings. We show that the effects of government spending decay sharply in space. An additional dollar of defense spending increases retail spending by \$0.31 in zip codes within a 10-mile radius, \$0.07 between 10-25 miles,

[2] The correlation coefficient between our measure and county-level retail sales from the Economic Census is 0.95 (0.99 with state-level retail and restaurant expenditures from the BEA's Personal Consumption Expenditure Series).

$0.006 between 25 and 50 miles, and has no detectable effect beyond 50 miles. We also find that the impact of nearby DOD spending varies across store categories. Much of the effect is driven by the two largest categories in the data—restaurants and grocery stores—and the impact on restaurant spending is more spatially concentrated around the location of the DOD contract relative to other retail categories. When we repeat the analysis using raw counts of cell phone visits, we find qualitatively different results, which even flip signs in some specifications.

The primary contribution of our paper is to provide a validation study of the foot traffic and payment card data for measuring retail consumption.[3] We show that both data sources have strengths and weaknesses and develop a methodology that combines them to measure local consumption more accurately. The comparison exercises we perform here may be useful for other researchers using similar data.

We also contribute to a large and well-established literature in macroeconomics that measures the multiplier effects of government spending. Our empirical approach closely follows Auerbach et al. (2020), who study the impact of DOD spending on employment at the city level. However, our data are significantly more disaggregated, allowing us to measure how fiscal multipliers vary spatially and across retail categories. Another close paper is Dupor et al. (2023), who study the impact of spending shocks at the county level using data on retail spending from Nielsen.[4]

We describe the data in detail in Section 2, and we discuss our approach to measure local spending in Section 3. We illustrate the use of this local spending measure in Section 4, which presents our findings regarding the effect of fiscal spending on consumer retail spending at the zip code–NAICS level and discusses other applications for these data. The paper concludes in Section 5.

[3] Chen and Pope (2020) show that the Safegraph panel is broadly representative of the U.S. population but do not consider how cell phone visits map to consumer expenditure.

[4] A number of other papers document heterogeneity in fiscal multipliers across other dimensions, including across countries (Auerbach and Gorodnichenko, 2013), business cycle conditions (Auerbach and Gorodnichenko, 2012; Ramey and Zubairy, 2018), and the type of government spending (Ilzetzki et al., 2013) (see Ramey (2019) for a recent survey).

2 Data

In this paper, we combine a number of different datasets. We briefly describe these here and provide additional details in Appendix A.

We obtain cell phone foot traffic from Safegraph for the entire United States during 2018 and 2019 (Safegraph, 2018-2019). Safegraph is a company that provides aggregated, de-identified location data collected from a panel of smartphones. The data provided to us include the monthly count of visits and unique visitors to a set of 18M points of interest (which include both retail stores and other places like hospitals, churches, transit stations, etc; Safegraph 2024a). Safegraph counts a "visit" as a series of smartphone pings within the polygon that corresponds to a point of interest. Safegraph also provides a set of attributes associated with the points of interest, including its brand, North American Industry Classification System (NAICS) category, and zip code. The Safegraph location data was made widely available for research during the COVID-19 pandemic and has been used extensively by academic researchers in economics and other fields.

Our second primary data source contains credit and debit card transactions from a large payment card network. Each row in these data is a transaction between a cardholder and a merchant. We observe the transaction amount, the date, a merchant identifier (which is linked to a NAICS classification), and the zip code. We limit our analysis to transactions that occur at brick-and-mortar retail stores and restaurants.[5] In contrast to the Safegraph data, payment card expenditure data remains difficult to access.

There are two restrictions on the use of these data. First, we are required to aggregate the payment card data prior to merging it with the foot traffic data, so we are unable to make firm-level comparisons. We merge the aggregated data at the zip code–NAICS level. The payment card data provider also requires that any zip code–NAICS cell contain at least five merchants, with no merchant making up more than 50% of transactions.[6] Second, we are restricted from disclosing the absolute amount of transactions or sales in a zip code-NAICS combination, so we convert their values to an index by dividing by a constant. We then scale

[5] This includes 11 3-digit NAICS categories. Retail stores are defined by two-digit NAICS codes 44 and 45, and restaurants have three-digit NAICS code 722.

[6] The zip code–NAICS observations that meet these criteria make up 89% of transactions and 88% of expenditures.

the indexed values using publicly available estimates of the card provider's total payment volumes to obtain an estimate of spending. This transformation preserves the relative value of transactions and sales across zip codes and NAICS categories. We provide additional details of this calculation in Appendix A.

In Sections 3.1 and 3.2, we perform our analysis using the sample of matched zip code–NAICS observations, which cover 16,742 zip codes. We present summary statistics of the matched sample in Table A2. When we construct overall estimates of spending using the foot traffic data, we use all zip codes where Safegraph data are available because the restrictions described above do not apply to this step. Thus, the final data that we use to measure consumption is not affected by potential censoring.

To measure payment card use across different populations, we use the Diary of Consumer Payment Choice (DCPC), administered by the Federal Reserve Bank of Atlanta (Federal Reserve Bank of Atlanta, 2018). The DCPC surveys a nationally representative panel of US consumers about their use of payment instruments across purchase categories. We use the 2018 iteration of the survey, which includes 2,131 respondents who made retail purchases. The survey also contains information about respondents' income, state of residence, and age.

Our analysis incorporates several other auxiliary government data sources that we use as additional points of comparison. To compare coverage across store categories and geography, we use the Personal Consumption Expenditures series from the Bureau of Economic Analysis (BEA) (Bureau of Economic Analysis, 2018-2019) and retail sales from the 2017 Economic Census (U.S. Census Bureau, 2017). To compare the distribution of spending across demographics, we use spending in retail categories in the Consumer Expenditure Survey (CEX) (Bureau of Labor Statistics, 2019). We also use demographic information, including household median income, racial composition, and age, at the zip code level from the 5-year estimates of the American Community Survey (ACS) (U.S. Census Bureau, 2019).

In our empirical application, we use government expenditures computed from DOD contracts assigned between 2015 and 2019, which are available at USAspending.gov (U.S. Treasury, 2015-2019). These data are available at the contract level and contain the zip code of the contractor, the total dollar amount of the contract, and its duration. We closely follow the procedure described in Auerbach et al. (2020) and Demyanyk et al. (2019) to allocate contract spending over the duration of the project, and then aggregate this data at the zip code-year level.

3 Measuring local spending

This paper has three main objectives. We first present evidence related to the similarities and differences that exist between foot traffic and payment card data. Through these comparisons, we highlight the benefits and shortcomings of the two sources for measuring consumer spending. Second, we consider how a researcher might use the foot traffic data to proxy for consumer spending. To do this, we construct a set of weights that can be applied to these data to transform foot traffic into total expenditures. We compare the transformed data to estimates available from government sources. Finally, we use our transformed foot traffic data to examine a core question in macroeconomics: what is the size of the fiscal multiplier? We leverage the granularity of our transformed data to explore this question at the zip code level, which allows us to quantify how the impacts of government spending decay across space.

3.1 Comparing the foot traffic and payment card data

While a large (and growing) share of consumer spending occurs on credit and debit cards, analysis of raw card expenditures may still offer an incomplete view of overall consumption. Credit and debit card usage is correlated with both household demographics and purchase type. For example, Cubides and O'Brien (2023) report that households with income under \$25,000 used credit and debit cards for about 41% of all payments, compared to 68% among households that made over \$150,000.[7] Non-cash payments (including payment cards) accounted for about 82% of general merchandise purchases in the 2022 survey, but only 72% of fast food transactions.

Selection issues in the foot traffic data (collected from cell phone pings) appear to be less pronounced. Chen and Pope (2020) report that the Safegraph panel, in particular, is

[7]Selection appears to occur primarily along the intensive margin—the survey reports that 97% of consumers had at least one debit, credit, or prepaid card.

broadly representative of the US population. However, the foot traffic data measures visits rather than transactions or expenditure. If the ratio of visits to transactions or expenditures differs systematically across demographics or store categories, using foot traffic as a proxy for consumption may introduce its own bias. For example, both "window shoppers" who do not make a purchase and big spenders will register as equivalent visits in the Safegraph data. Foot traffic data may also suffer from measurement issues; Safegraph collects noisy GPS location pings and then attributes sequences of pings to visits (Safegraph, 2024b). These data may systematically miss certain types of purchases, such as transactions that occur quickly or those that occur in business-dense indoor locations (e.g., malls or shopping centers) where pings may be more difficult to attribute to a single store.

An initial look at the data shows that the Safegraph and payment card data are positively, but imperfectly, correlated across zip codes. Aggregated across categories, the correlation coefficient between total Safegraph visits and card transactions (spending) is 0.89 (0.82). Correlations between visits and spending within categories, which we show in Appendix Table A5, are also positive but well below one, ranging from 0.45 (electronics and appliances) to 0.85 (restaurants).

We then look deeper into these differences. We first compare the distribution of visits (from Safegraph) and transactions and expenditures (from payment cards) to retail spending as reported in the CEX. Figure 1 shows this distribution across deciles of median zip code household income, where each decile is constructed so that it contains an equal share of the population. We match the CEX data to these deciles by computing per-capita spending for respondents with income in the decile range. Safegraph visits are nearly uniformly distributed across deciles, while payment card activity is much more concentrated in higher income places; the highest decile contains about 17% of total expenditures and 14% of transactions, compared to 5% and 7% in the lowest decile.[8] The spending distribution from the CEX lies in between the payment card and foot traffic series.

We then compare the distribution of economic activity in the Safegraph, payment card,

[8] In Appendix Figures A1-A3, we show several additional comparison plots by deciles of median age, racial composition, and population density. These show that, relative to the payment card data, a higher share of Safegraph activity occurs in zip codes that are younger and less white.

and BEA data across 7 NAICS categories in Figure 2.[9] Restaurants are the largest category in both the Safegraph and card data, accounting for about 60% of transactions and visits and 42% of card spending but a significantly smaller fraction of BEA spending. Gasoline accounts for 14% of card transactions but only 10% of visits, which is consistent with the foot traffic data undercounting quick transactions. Grocery stores also tend to make up a larger share of payment card activity (19% of transactions and 23% of spending) relative to Safegraph visits (12%).

We note that the differences we show above do not prove that one source or another offers a more accurate measure of local consumption. For example, the pattern in Figure 1 could reflect more severe selection on income in the payment card data relative to the foot traffic data. However, it could also be the case that high-income consumers visit stores at the same rate as low-income consumers but are more likely to transact and spend more per transaction (consistent with the consumption patterns shown in the CEX). Rather, we take these plots as evidence that which measure a researcher uses can have an important impact on their empirical results.

3.2 Creating weights to transform the foot traffic data

We then estimate weights that will allow us to transform the foot traffic data to approximate spending data in three steps. We first construct an estimate of overall retail spending from the card expenditure data. The implicit assumption in this exercise is that the spending patterns that we observe are representative of that of spending on other (unobserved) payment card networks. We then explicitly correct for selection into who uses a credit or debit card by combining our data with the Diary of Consumer Payment Choice. This yields an estimate of overall spending across all payment methods by zip code and NAICS category. Finally, we estimate the relationship between Safegraph visits and payment card expenditures. The output is a set of weights that can be applied to the aggregated Safegraph data to estimate spending at the zip code–NAICS level.

[9]The shares of visits, transactions, and dollars in Figure 2 sum to one across the 7 categories included in the figure. We report the distributions for all 11 NAICS categories in Table A2, of which only 7 have analogues in the BEA data.

3.2.1 Scaling up payment card data

Our starting point is to recognize that we observe credit and debit card spending at the zip code–NAICS level *only* among cards issued by our data provider, which does not include payments on other card networks or with other payment instruments, such as cash. We label this variable as $sales^{card}_{n,z}$, with n denoting the 3-digit NAICS category and z the zip code. We proceed by scaling up the observed spending to get an estimate of the total in two steps.

We first inflate the observed spending to account for activity on other payment networks, assuming that our measure of spending is representative of other credit and debit cards. We get the market share of the data provider in 2019 from McCann (2023), which we refer to as sh^{card}. We then compute spending on all card networks as $sales^{card}_{n,z} \times 1/sh^{\text{card}}$. In the second step, we account for spending that occurs by other payment methods. To do this, we estimate the share of spending that occurs on cards from the DCPC.

A primary concern in using card data to approximate consumption is that there may be selection into who uses credit or debit cards. Our approach explicitly accounts for this selection by allowing the share of spending on payment cards to vary across both consumer demographics and purchase categories. We denote our estimate of the card share of spending in zip code z and NAICS n as $sh^{\text{all cards}}_{n,z}$, and discuss how we estimate it below.

The DCPC classifies purchases into four categories: restaurants, grocery stores, retail gas stations, and a composite "other," which includes all other retail NAICS. The DCPC also reports the state of residence (which we aggregate to Census division) and discretized household income of the respondent.[10]

We first compute the individual-level share of spending on cards for each DCPC respondent by NAICS group. We then regress spending shares on Census division fixed effects, income bracket fixed effects, and NAICS fixed effects. This is, we estimate

$$sh_{n,i} = \alpha_s + \alpha_y + \alpha_n + \mu_{n,i}, \tag{1}$$

where $sh_{n,i}$ is individual i's spending share in NAICS n on cards, and α_s, α_y, and α_n denote Census division, income group, and NAICS fixed effects; $\mu_{n,i}$ is the error term.

[10]We aggregate the income bins to four categories: <35k, 35-75k, 75-100k, and >100k.

We report the estimates of Equation 1 in Table A6. As expected, we find that the share of spending on payment cards is increasing in income; households with income above \$100k do 27 percentage points more of their spending by card than those with income below \$35k. While the breakdown of purchases by category in the DCPC is somewhat limited, we do find that card share is about 14 percentage points lower for restaurants than other types of stores.

After estimating Equation 1, we use the results to predict the share of spending on cards for zip code z and NAICS n from zip code-level demographics. Specifically, we denote the share of zip code z's population that falls in income bracket y by $p_{y,z}$, which we obtain from the ACS. We also denote the average consumer-level retail spending by income group d_y, which we obtain from the DCPC. With these in hand, we aggregate the income bracket fixed effects α_y for each zip code z by the share of spending in that zip code that corresponds to income group y:

$$\hat{sh}_z^y = \frac{1}{\sum_y d_y} \sum_y p_{y,z} \times d_y \times \hat{\alpha}_y.$$

We then predict the share of spending on cards for NAICS n in zip code z:

$$\hat{sh}_{n,z} = \hat{\alpha}_s + \hat{\alpha}_n + \hat{sh}_z^y,$$

and use $\hat{sh}_{n,z}$ to generate our estimate of total spending across all payment methods:

$$\hat{sales}_{n,z} = sales_{n,z}^{card} \times 1/sh^{card} \times 1/\hat{sh}_{n,z}.$$

3.2.2 Using foot traffic data to measure local spending

With a measure of zip code–NAICS total spending in hand, we turn to generating a set of weights, or scaling factors, that can be used to estimate spending from foot traffic data. We view these weights as an important research output of this project; researchers across many fields are widely using data from Safegraph and other providers, while card spending data remains more difficult to access. The scaling factors that we produce can be used to improve estimates of local consumption relative to a more naive measure available from the foot traffic data (e.g., simply computing the sum of visits by zip code). Such an approach may yield biased estimates if spending per visit varies systematically across zip codes and categories. Our methodology addresses this concern by directly estimating the ratio between visits and spending.

We start from the Safegraph data, aggregated by zip code–NAICS–year, which we denote by $v_{n,z}$. Using this and our measure of total spending, we construct the ratio of sales to visits: $dv_{n,z} = \frac{s\hat{ales}_{n,z}}{v_{n,z}}$. We display summary statistics of this ratio by NAICS in Table A7; the median zip code has about \$800 of total spending for each visit, with significant variation across zip codes and store categories.

We then estimate a Poisson regression of $dv_{n,z}$ on a set of controls for each year.[11] We include zip code-level demographics obtained from the American Community Survey (2019), including median income, median age, the share of the population that is white, and population density. We create dummies for quartiles of each demographic variable, and we add to this set of controls state and NAICS fixed effects. The pseudo-R^2 of this regression is around 0.35; we report coefficients in Table A8. We use these estimates to predict $\hat{dv}_{z,n}$, which is our object of interest: a set of weights that transform foot traffic data into a measure of total retail spending. We then compute *estimated* consumer spending in zip code z and NAICS n as $ls_{n,z} = \hat{dv}_{n,z} \times v_{n,z}$, which we use in our application. Importantly, because in this step we use zip code level information from the American Community Survey, we can compute $\hat{dv}_{z,n}$ for every zip code in the United States with recorded Safegraph visits, including those for which payment card data are not available due to censoring.

In Figure A4, we show the distribution of estimated spending by income decile along with the distribution of raw card spending and CEX consumption. The results show that our adjusted spending measure reduces the share of spending in the top decile and increases the share in the lowest decile, moving both closer to estimates from the CEX. This reflects patterns from the DCPC that show that card usage is increasing in income.

We validate our measure of estimated spending by comparing it to two government sources: retail and restaurant expenditures from the BEA Personal Consumption Expenditure series (available at the state level) and retail sales from the 2017 version of the Economic

[11] The Poisson specification yielded a better fit relative to linear models.

Census (available at the county level). The results (in Figures 3a and 3b) show that our constructed measure of spending closely matches these government sources, with a correlation coefficient at the county level of about 0.95 and at the state level of 0.99.

3.2.3 Discussion

Given the lack of easily available, geographically granular consumption data, we believe that our spending measure fills an important gap and may be useful for a broad range of empirical applications (we present one possible use and discuss others in Section 4). However, as with any data source, there are natural limitations. In this section, we outline some of these pitfalls and provide practical guidance for researchers on when and where use of these weights may be appropriate.

First, we compute the spending weights described above using 2018 and 2019 data. As the scope and coverage of cell phone location data grows over time, these weights may no longer map to consumer spending in other years. Correcting for growth in the number of devices in the Safegraph panel is straightforward through a simple rescaling if that growth is relatively uniform across geography and demographic groups.[12] However, if selection into the Safegraph panel changes, or if the relationship between foot traffic and expenditures in a given store category is fundamentally altered (for example, during the COVID-19 pandemic), the weights used here may not be appropriate to measure aggregate retail consumption. A similar caveat applies for researchers considering applying the weights to cell phone location data from other providers.

Second, in creating the spending weights, we combine data from several sources, which may introduce measurement error at various stages. Our exercise utilizes survey data from the DCPC to measure the propensity of consumers to use cards. While the DCPC is nationally representative, it measures the behavior of only a few thousand respondents, which limits the degree of heterogeneity we can measure along this margin.[13] Additionally, restrictions imposed by the payment card company limit us from analyzing small zip codes with fewer

[12]For example, our weights could be applied to Safegraph data from a different year to compute zip code–NAICS spending, then scaled so that the total matches national retail sales from the BEA's PCE series.

[13]For example, equation (1) includes Census division fixed effects rather than state fixed effects and assumes that these enter additively with income.

than five stores. Thus, these zip codes are not included in the *estimation* of the weights.[14] Further, as we note in the data section, the Safegraph data itself is likely to contain noise due to the nature of aggregating location pings into visits.

Despite these potential sources of error, we are comforted by the fact that our estimated spending measure matches remarkably well with government retail spending data at the county and state level (see Figures 3b-3a). In addition, in Section 4, we show that using an aggregated version of our data to estimate government spending multipliers gives estimates that are in line with those reported by prior literature.

4 Application: estimating local fiscal multipliers

In this section, we apply the weights we constructed in the previous sections to examine a classical question in economics: What is the effect of fiscal spending on economic output? This question is often referred to as quantifying the fiscal multiplier associated with government spending. Existing literature has measured fiscal multipliers at the MSA, county or state level. However, if government spending is localized, as in government procurement contracts, its effects may be highly heterogeneous across space within a larger geographic unit. The degree to which the shock propagates across space depends on residential and firm sorting, commute patterns, or other local variables. To our knowledge, ours is the first paper to measure multipliers at the zip code level.

Our analysis closely follows the empirical approach from Auerbach et al. (2020). More specifically, they estimate how Department of Defense (DOD) spending impacts city-level output, earnings, and employment data. We adapt their approach to our more granular data to study how these same spending shocks impact retail spending.

In addition to the level of geographical aggregation of the data, there are other differences between our application and that of previous work. First, because the Safegraph panel is relatively new, we focus on the 2018-2019 period. Though, in principle, we could extend the analysis to later years, the COVID pandemic limited the extent to which consumers visited

[14] As we describe above, we are still able to impute weights $\hat{dv}_{z,n}$ even for these missing cells, and so they are not dropped from the measure of aggregate spending.

retail locations, thus preventing us from using visits data to generate a measure of local spending. Second, the restriction to two years also affects the equation that we estimate, which we describe below.

We first replicate the city-level analysis from Auerbach et al. (2020) using our retail spending data, which we show in Table A9. Our preferred specifications (in columns (2) and (4)) show that a \$1 increase in spending between 2017 and 2018 was associated with an increase in retail spending one year later between \$0.17 and \$0.19, which are in line with previous estimates (although we note these are imprecisely estimated). For example, Dupor et al. (2023) report that a \$1 spending shock increases county-level nondurable spending by \$0.29, while Auerbach et al. (2020) report an effect of \$0.35 on labor earnings. Appendix B reports estimates for the effect of lagged values of DOD spending shocks.

We then turn to examining how the effects of government spending propagate spatially. If gains to the local economy from additional spending are very localized, the choice of where contracts are awarded can have important allocative and distributional effects, even within a city.[15] To study this question, we regress the growth of consumer spending in nearby zip codes on changes in DOD spending at various distance intervals. Our estimating equation is:

$$\frac{ls_{2019,d(\mathbf{z})\leq 10} - ls_{2018,d(\mathbf{z})\leq 10}}{ls_{2018,d(\mathbf{z})\leq 10}} = \beta_0 + \sum_{k \in \text{Dist. bin}(z)} \beta_{k(\mathbf{z})} \frac{\Delta DoD_{2018,k(\mathbf{z})}}{ls_{2018,d(\mathbf{z})\leq 10}} + \varepsilon_z, \qquad (2)$$

where $ls_{t,d(\mathbf{z})\leq 10}$ denotes *estimated* consumer retail spending in year t within 10 miles of zip code z and $\Delta DoD_{2018,k(\mathbf{z})}$ refers to the change in DOD spending between 2017 and 2018, within distance bin $k(\mathbf{z})$ from zip code z. In estimation, we define four distance bins surrounding zip code $\mathbf{z}$: within 10 miles, between 10 and 25 miles, between 25 and 50 miles, and between 50 and 100 miles.

We define the dependent variable as the growth in retail expenditure between 2018 and 2019, while we compute the independent variables as the change in DOD spending between

[15]More granular estimates of the fiscal multiplier may also help to distinguish between competing models of the business cycle (Nakamura and Steinsson, 2018).

2017 and 2018; this is to capture the full effects of DOD contracts that begin partway through the year.[16] The coefficients β_{10}, β_{25}, β_{50}, and β_{100} capture how a change in DOD spending at each respective distance affects retail expenditures in zip codes within 10 miles of zip code z.

We report our estimates of Equation 2 in Table 1. Our dependent variable is defined as a percentage change, so places with low initial levels of spending in 2018 can result in large outliers. We deal with this by trimming the top and bottom of 1% of observations (columns (1) and (2)) or alternately weighting observations according to their spending in the base year (columns (3) and (4), our preferred specification). Columns (1) and (3) present OLS estimates and show that the impact of DOD spending decays quickly with distance. Column (3), for instance, shows that \$1 of additional DOD spending within 10 miles increases retail spending by about \$0.08. If the spending instead occurs between 10-25 miles or 25-50 miles, it increases retail expenditures by \$0.035 or \$0.002, respectively. The effect of spending further than 50 miles is statistically insignificant and very small in magnitude.

Prior literature has raised the concern that changes in DOD spending may be correlated with time-varying unobservable factors that also impact local spending, which would create an endogeneity problem in estimating Equation 2 via OLS. Nakamura and Steinsson (2014) and Auerbach et al. (2020) discuss several reasons for this: government spending changes may be affected by political considerations or could be anticipated by large defense contractors, among others. To deal with this potential issue, we adopt the instrumental variable strategy used in both of these papers. Specifically, we construct Bartik-style instruments using the share of national DOD spending between 2015 and 2019 that took place within various distance radii around zip code z. The instruments are defined as

$$\frac{s_{k(\mathbf{z})} \times (DoD_{2018} - DoD_{2017})}{ls_{2018,d(\mathbf{z})\leq 10}}$$

where $s_{k(\mathbf{z})}$ is the share of national 2015-2019 DOD spending that occurred between in distance interval $k(\mathbf{z})$ around z and DoD_t is the total amount of DOD spending in year t. We construct four instruments based on the four distance bins discussed above.

[16] Table A9 also reports specifications that include additional DOD spending lags.

Columns (2) and (4) in Table 1 show estimation results of Equation 2 using the IV strategy described above. The IV estimates are associated with larger standard errors than the OLS version. Column (2) presents the trimmed version, which shows that spending in the closest distance bin returns a negative and insignificant point estimate. In column (4), we show results from a weighted specification, which shows a larger and statistically significant coefficient; an additional \$1 of DOD spending increases retail spending by about \$0.31 within 10 miles, by \$0.07 between 10 and 25 miles, and by \$0.006 between 25-50 miles.

We then conduct the same analysis by NAICS category, focusing on our preferred specification that uses Bartik-style IVs and weights observations by their 2018 level of spending. We show the results in Table 2 for the five largest store categories in the data. We find that much of the overall retail spending effect is driven by restaurants and grocery stores, the two largest categories in our data. The results also show interesting heterogeneity in how quickly the spending effects decay in space. Moving \$1 of DOD spending from within 10 miles to between 10 and 25 miles reduces the impact on restaurant spending by 75%, relative to 54% for grocery stores. For gas stations, we actually estimate a larger coefficient on spending between 10 and 25 miles than for spending within 10 miles (although these are somewhat imprecisely estimated). These differences across categories may be driven by contracted firm workers who visit restaurants near their offices but tend to purchase gasoline and shop in more distant neighborhoods.

Finally, in Table A10, we show that estimating Equation 2 using the unadjusted foot traffic data as a proxy for consumer retail spending, instead of the estimated one introduced in the previous section, leads to coefficients that are qualitatively different, and even have the opposite sign. Specifically, a \$1 increase in DOD spending within 10 miles is associated with a *decrease* in total visits within 10 miles in unweighted specifications (columns (1) and (2)) or a small increase in the weighted versions (columns (3) and (4)). Predictions of how quickly retail activity decays spatially also differ substantially from our main specification.

In this section, we have illustrated one of many possible applications of our spending weights. This data may serve as a valuable complement to existing data sources for research projects in empirical urban economics, macroeconomics, household finance, or other fields. Existing work measuring consumption responses to macroeconomic shocks has largely used individual data from the CEX (Anderson et al., 2016; Coibion et al., 2017; Chang and Schorfheide, 2024) or regional employment data as a proxy for consumption at a higher level of aggregation (Chodorow-Reich et al., 2021; Guren et al., 2021; Mian et al., 2013). While the CEX has the important advantage of being available at the individual level, the sample size is relatively small compared to the Safegraph panel, which may be a limitation for certain applications.[17] Relative to local employment data, the re-weighted Safegraph data is a more direct measure of consumption and can be computed at the zip code–NAICS level (rather than aggregated across industries at the state or county level), but is available over a much shorter time frame than many government-provided series. Studies of place-based policies, which have largely examined effects on investment and labor markets, may also benefit from this type of data (Busso et al., 2013; Neumark and Young, 2019). The advantages and disadvantages of our consumption measure relative to other sources will, of course, depend on the specific application; nevertheless, we believe it may be a useful element in the toolbox of empirical researchers across a diverse set of fields.

5 Conclusion

In this paper, we compare two promising and increasingly popular sources of consumption data: payment card transactions and cell phone location pings. We find that the two data sources are positively, but imperfectly, correlated. Spending data from credit and debit cards may suffer from selection on income and other demographics and are not widely available to researchers. Cell phone location data are more easily accessed but do not directly measure spending. We develop a methodology that addresses these issues to create an improved proxy for local consumption. After aggregating this measure, we show that it matches well with government data on consumer spending, which is reported at the county and state levels. We then illustrate an application of these data by measuring the impact of government spending on local consumption. Our results show that an additional dollar of DOD contracting increases local retail expenditures, but the effect decays quickly across

[17] For example, McKay and Wolf (2023) addresses this point directly in the context of studies of the effects of monetary policy on consumption, arguing that lack of statistical power due to sampling variation in the CEX has been an important empirical challenge.

space. Further, our findings also show that using foot traffic data as a proxy for consumer spending leads to qualitatively different estimates of the impact of government spending on local consumption.

Granular consumption data may be useful for studying a wide range of policies with localized impacts. In contrast to traditional government sources, cell phone location data is available at a much finer spatial and temporal aggregation level. We hope that the initial analysis we show in this work will enable future researchers to conduct similar analyses to study a host of important national and local policies.

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Tables and figures

Table 1: Effect of Department of Defense spending by distance thresholds

	(1)	(2)	(3)	(4)
DoD spending within 10 miles	0.0979	-0.0553	0.0727	0.307
	(0.0306)	(0.0620)	(0.0139)	(0.0763)
DoD spending between 10 and 25 miles	0.0164	0.0445	0.0344	0.0704
	(0.00329)	(0.0110)	(0.00547)	(0.0247)
DoD spending between 25 and 50 miles	0.00171	0.00290	0.00241	0.00589
	(0.000483)	(0.000997)	(0.000526)	(0.00111)
DoD spending between 50 and 100 miles	0.0000255	-0.0000967	0.00000777	0.0000165
	(0.0000636)	(0.0000904)	(0.00000508)	(0.0000117)
Constant	0.153	0.152	0.0878	0.0858
	(0.000662)	(0.000799)	(0.00183)	(0.00196)
1% Trim	Yes	Yes	No	No
Weighted Regression	No	No	Yes	Yes
IV	No	Yes	No	Yes
Observations	30,703	30,703	33,083	33,083

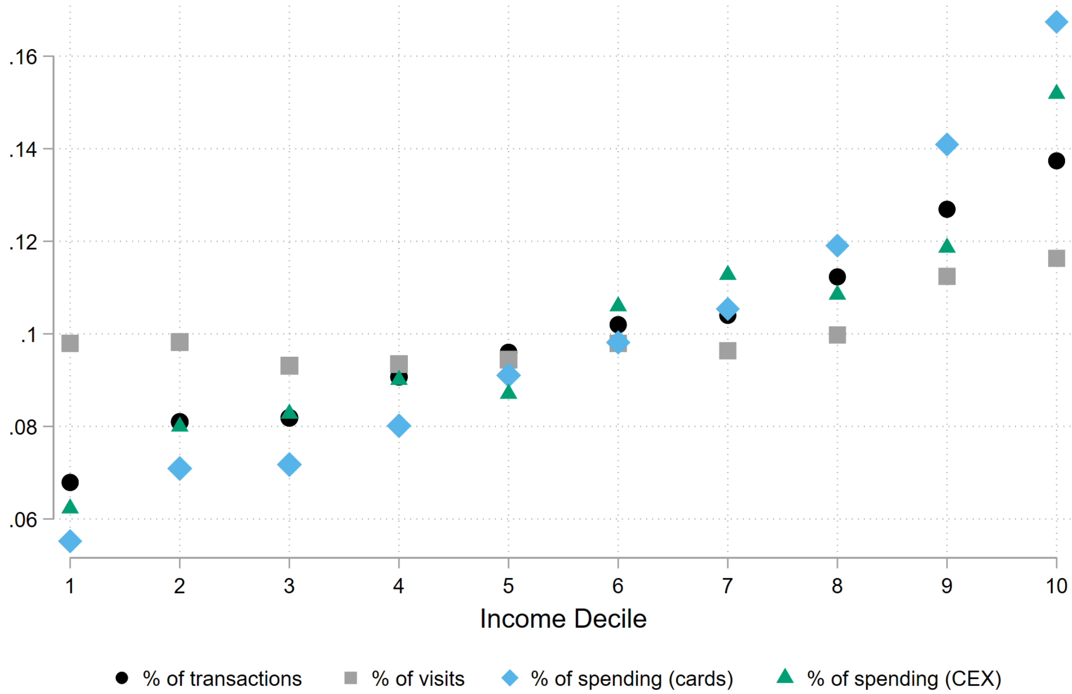
Note: The table shows results from estimation of Equation 2. The dependent variable is the 2018-2019 percentage change in estimated retail spending within a 10-mile radius of a zip code. Columns (1) and (3) report results from an OLS regression, while (2) and (4) instrument for DOD spending with a Bartik-style instrument. The first-stage F tests range between 29.14 and 138.64.

Table 2: Effect of Department of Defense spending by distance thresholds and NAICS category

	Restaurants	Food Stores	Gas Stations	General Merchandise	Clothing
DoD spending within 10 miles	0.204	0.0485	0.00501	-0.0344	0.00404
	(0.0397)	(0.0125)	(0.00344)	(0.00944)	(0.00187)
DoD spending between 10 and 25 miles	0.0512	0.0216	0.00635	0.00126	0.00124
	(0.00848)	(0.00432)	(0.00117)	(0.000892)	(0.000285)
DoD spending between 25 and 50 miles	0.000639	0.000245	0.00148	0.0000906	0.0000580
	(0.000158)	(0.000139)	(0.000247)	(0.000105)	(0.0000470)
DoD spending between 50 and 100 miles	0.000122	0.000199	0.0000113	0.000105	0.0000113
	(0.0000600)	(0.0000390)	(0.00000649)	(0.0000447)	(0.00000738)
Constant	0.0839	0.0705	0.0414	0.176	0.0943
	(0.00238)	(0.00220)	(0.00146)	(0.00142)	(0.00150)
Observations	31,301	30,543	30,436	28,369	24,032

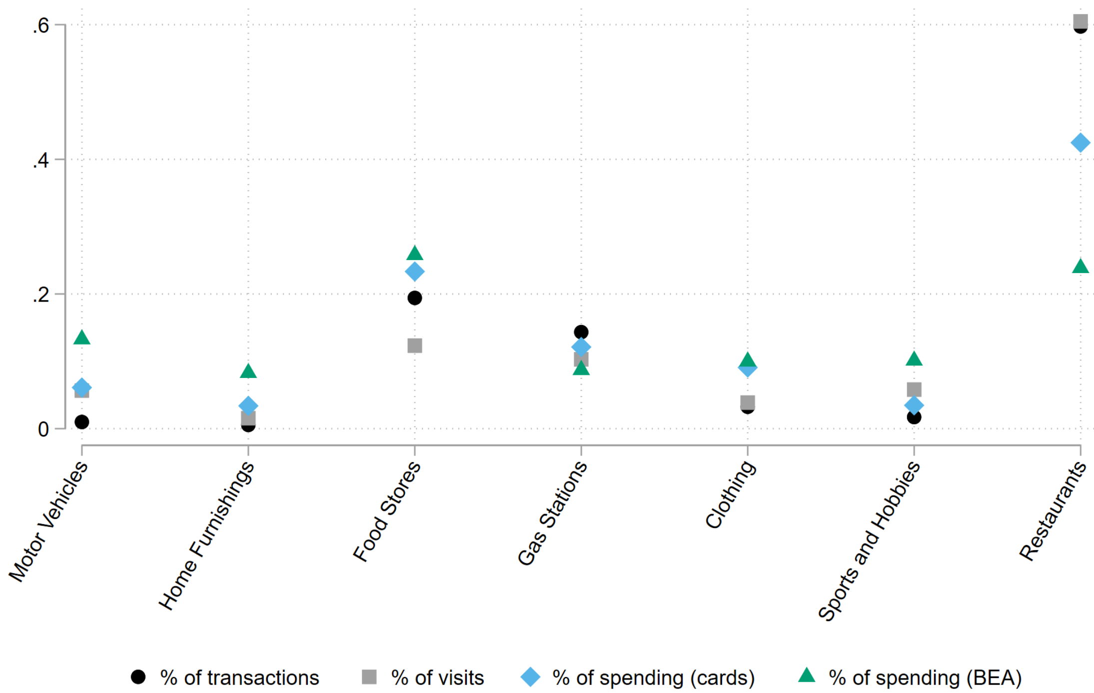
Note: The table shows results from IV estimation of Equation 2 by store category for the top five categories in the data, where observations are weighted by their total spending in the base year. The dependent variable is the 2018-2019 percentage change in estimated retail spending within a 10-mile radius of a zip code in a given NAICS. All columns instrument for DOD spending with a Bartik-style instrument. The first-stage F-tests for Restaurants range between 24.12 and 45.28, for Food Stores between 12.39 and 27.64, for Gas Stations between 32.16 and 238.92, for General Merchandising between 9.63 and 44.68, and for Clothing between 4.65 and 53.77.

Figure 1: Share of foot traffic, transactions, and spending by income decile



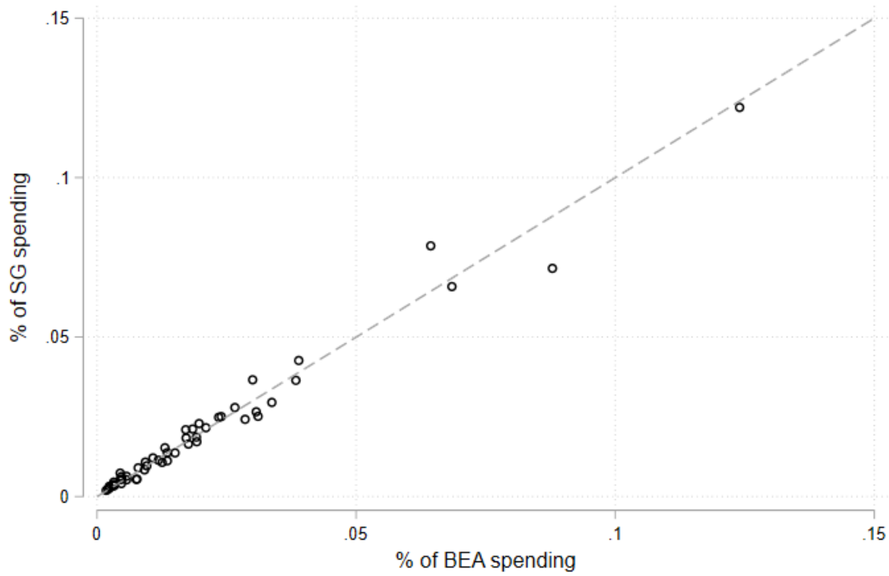
Note: The figure shows the distribution of economic activity in 2018 and 2019 across income deciles categories as measured in the payment card data (in transactions and spending), the Safegraph data (visits), and the CEX data (spending). Income deciles are defined based on zip code-level median household income using the set of matched payment card-Safegraph data so that each decile contains 10% of the population. We match the CEX data to these deciles by aggregating observations that fall in the income range of each decile and computing average spending per respondent in retail categories.

Figure 2: Share of foot traffic, transactions, and spending by NAICS

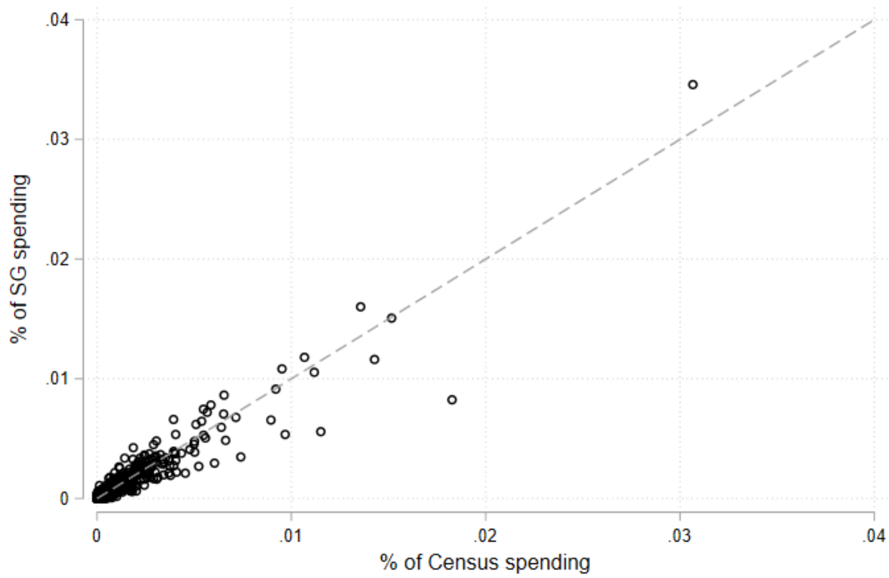


Note: The figure shows the distribution of economic activity in 2018 and 2019 across 7 NAICS categories as measured in the payment card data (in transactions and spending), the Safegraph data (visits), and the BEA data (spending).

Figure 3: Distribution of adjusted spending compared to government sources



(a) State-level data (BEA PCE)



(b) County-level data (Economic Census)

The figure compares the measure of consumer spending constructed with our proposed methodology to two government sources. Panel (a) shows the distribution relative to the share of retail and restaurant spending in each state computed from the Personal Consumption Expenditures series from the Bureau of Economic Analysis. Panel (b) shows the share of retail spending (excluding restaurants) in each county computed from the 2017 version of the Economic Census. Each dot in the two figures is a state or county; the grey dashed series is the 45-degree line. The correlation coefficients are 0.99 in panel (a) and 0.95 in panel (b).

Online Appendix

A Data and supplementary descriptive results

Foot traffic data

The foot traffic data comes from Safegraph, a company that collects aggregated location data from smartphones. This data includes counts of visits and unique visitors to a set of points of interest across the United States in 2018 and 2019. Each point of interest is associated with a NAICS code, a brand identifier, an address (including zip code), and a NAICS category. We further aggregate this data at the zip code–NAICS level prior to merging with the payment card data. Over the two-year sample period, the data covered about 12B visits in 30,936 zip codes. We show summary statistics on the sample by NAICS category in Table A1.

Payment card data

The credit and debit card expenditure data is provided by a major payment card network. The sample used for this project includes all US brick-and-mortar card transactions in 2018 and 2019. The underlying data is stored at the transaction level, with each row representing a payment between a cardholder and a merchant. On the merchant side, we observe a numeric identifier, the merchant's name, the zip code of the store, and the merchant's 3-digit NAICS code.

All analysis of the card data for this project is done at the zip code–NAICS level to comply with the data use agreement. This prevents us from doing analysis at the store level. In addition to this aggregation requirement, we observe two other restrictions:

1. Each zip code–NAICS cell must contain at least five merchants and ten accounts and have no single merchant make up more than 50% of sales or transactions. We are unable to merge zip code–NAICS observations that do not meet these criteria to the Safegraph data. The observations that comply with this restriction account for 89% of transactions and 88% of expenditures.

2. We are unable to merge data that contain the raw number of transactions or dollars in a given zip code–NAICS cell. Instead, we convert the raw number of transactions and dollars to an index prior to merging by dividing the entire dataset by a constant. This conversion does not affect relative comparisons across NAICS categories, zip codes, or time. After exporting the data, we re-scale the index so that the sum of dollars and transactions match the estimated total US offline expenditures and transactions for the payment card network, which we compute using the following information:

   - We take the total US payment flows and transaction volumes reported in the payment card network's publicly available annual report for 2018 and 2019.
   - We assume that 53% of spending and transactions occur via brick-and-mortar purchases, per calculations using similar data in Dolfen et al. (2023).

We then merge the payment card data to the foot traffic data by zip code and NAICS. Table A2 reports summary statistics on the matched data (summed across both sample years) by NAICS category, including the number of zip codes, the distribution of transactions, spending, visits, and the average transaction size (computed as the sum of payment card spending divided by the number of transactions).

We use this matched sample for the comparison exercises in Section 3.1, as well as to compute the scaling factors, which we describe in Section 3.2. We then apply these scaling factors to the full set of Safegraph data, which includes all zip code–NAICS combinations where observe visits. We use this transformed data to compute fiscal multipliers in Section 4.

Diary of Consumer Payment Choice

To estimate the share of spending that occurs on credit and debit cards, we use the 2018 version of the Diary of Consumer Payment Choice (DCPC), administered by the Federal Reserve Banks of Atlanta, Boston, Richmond, and San Francisco. The survey asked a nationally representative set of respondents to keep daily records of their payments and cash management, including the dollar value, category, and payment instrument that was used, during a three-day period in October 2018. Respondents also answer questions about their demographics and household makeup, including annual income and state of residence. We aggregate the purchase categories reported in the DCPC to match the NAICS categories reported in the payment card and foot traffic data. The five purchase categories we include, along with their assigned NAICS categories, are listed in Table A3.

We consider only diary entries that are coded as purchases, which excludes other transactions like cash withdrawals, deposits and transfers. We further exclude purchases that do not map to our retail categories. We drop 20 respondents that did not report annual household income. We report summary statistics of this sample in Table A4.

DOD Contract Data

Our application uses government spending measured from DOD contracts. We download this data from USAspending.gov. We include all prime award contracts and indefinite delivery vehicles (IDVs) that were awarded by DOD, listed the place of performance as in the US, and were issued between 2015 and 2019. We follow the procedure described in Auerbach et al. (2020) and Demyanyk et al. (2019) in allocating contract spending uniformly over the duration of the contract.

Consumer Expenditure Survey

We compare the distribution of visits, spending, and transactions by income group to the Consumer Expenditure Survey (CEX) in Figure 1. The CEX is a survey administered by the Bureau of Labor Statistics that collects data on expenditures, income, and demographics. We use the 2019 edition, which contains 26,903 responses. We aggregate spending in the following categories as "retail", which map the NAICS categories we use in the payment card and Safegraph data: food at home, food away from home, household furnishings, major appliances, small appliances, apparel, vehicles, fuel, gasoline, medical supplies, pets, toys and hobbies, and reading.

To produce Figure 1, we define income deciles based on the set of matched Safegraph-payment card zip codes. We then compute spending in the CEX for each decile by taking the mean of retail spending among all participants that fall in the income range of the decile.

Appendix Table A1: Summary statistics for Safegraph sample

NAICS	NAICS descr.	Num. zips	# visits (M)	% visits
441	Auto parts	19,126	528	4.3%
442	Furniture	14,183	170	1.4%
443	Electronics	10,216	111	0.9%
444	Home improvement	19,991	414	3.4%
445	Grocery	22,670	1,152	9.4%
446	Pharmacy	15,095	509	4.1%
447	Gasoline	21,692	1,048	8.5%
448	Clothing	12,967	356	2.9%
451	Hobby/books	17,087	633	5.1%
452	Gen. Merchandise	16,984	1,276	10.4%
453	Misc. retail	18,934	891	7.2%
722	Restaurants	25,451	5,216	42.4%
Total		30,936	12,304	100.0%

Note: The table shows summary statistics on all zip code-NAICS combinations in the Safegraph data that contain a positive number of visits, as well as the distribution of visits across NAICS categories. The table combines visits in 2018 and 2019.

Appendix Table A2: Summary statistics for matched sample

NAICS	NAICS descr.	Num. zips	% spending	% transactions	% visits	Avg. ticket size
441	Auto parts	9,945	4.5%	0.8%	4.4%	178
442	Furniture	5,156	2.5%	0.5%	1.2%	182
443	Electronics	2,361	1.3%	0.2%	0.4%	207
444	Home improvement	5,965	4.5%	1.9%	2.7%	76
445	Grocery	11,770	17.3%	16.6%	9.5%	35
446	Pharmacy	6,864	2.9%	2.8%	3.7%	34
447	Gasoline	10,655	9.0%	12.2%	7.9%	25
448	Clothing	8,129	6.7%	2.8%	3.0%	82
451	Hobby/books	5,883	2.6%	1.5%	4.5%	59
452	Gen. Merchandise	5,680	13.6%	7.3%	8.9%	60
453	Misc. retail	11,264	3.7%	2.8%	7.6%	45
722	Restaurants	15,996	31.4%	50.6%	46.2%	21
Total		16,742	100.0%	100.0%	100.0%	

Note: The table shows summary statistics on matched zip code-NAICS combinations that are present in both the Safegraph and payment card data. Our analysis sample in the payment card data includes only zip code–NAICS combinations that contain at least five merchants and ten cardholders with no single merchant accounting for more than 50% of transactions, as we detail in Appendix A. The table also shows the distributions of spending, transactions, and visits across NAICS categories. The last column shows the average transaction size in the payment card data by category (computed as the sum of expenditures divided by the count of transactions). The table combines visits in 2018 and 2019.

Appendix Table A3: DCPC Purchase Categories

DCPC Purchase Category	Assigned NAICS
Grocery stores and convenience stores	445
Gas stations	447
Sit-down restaurants	722
Fast food restaurants	722
General merchandise, department stores, other stores	Other

Note: The table shows the correspondence between purchase categories reported in the DCPC and NAICS categories in the Safegraph and payment card data.

Appendix Table A4: Summary statistics for DCPC

	Card Spending	Cash Spending	Share of Card Spending	Observations
Panel A: Spending by Household Income ($)				
0 - 35,000	104.5	43.4	0.706	580
35,000 - 74,999	142.6	36.1	0.798	745
75,000 - 99,999	158.9	20.7	0.885	381
100,000+	207.0	24.4	0.895	688
Panel B: Spending by Age Group				
18 - 24	68.8	29.8	0.698	58
25 - 39	156.8	25.9	0.858	470
40 - 59	164.2	35.4	0.823	936
60 - 74	149.9	30.4	0.831	772
75+	144.1	39.2	0.786	158
Panel C: Spending by Store Category				
Grocery and pharmacy	51.3	8.5	0.857	1283
Gasoline	27.5	6.6	0.806	893
Sit-down Restaurants	35.7	9.2	0.795	603
Fast good Restaurants	11.8	6.1	0.659	929
Other retail	96.0	9.9	0.907	984
Panel D: Spending by Purchase Size ($)				
0 - 20	13.4	8.7	0.605	1801
20 - 99.99	74.6	15.6	0.828	1819
100 - 499.99	221.3	31.5	0.875	623
500 - 999.99	543.2	137.5	0.798	57
1,000+	1524.6	192.6	0.888	27

Note: The table shows summary statistics computed from the 2018 version of the Diary of Consumer Payment Choice by income group, age group, store category, and purchase size for transactions made with payment cards and cash. Spending, transactions, and card share are reported by survey respondents over a three-day period.

Appendix Table A5: Correlation coefficients across zip codes between the payment card and Safegraph data

	Visits vs. Transactions	Visits vs. Dollars
All	0.885	0.822
Motor Vehicles	0.707	0.692
Home Furnishings	0.519	0.612
Electronics and Appliances	0.476	0.451
Building Materials	0.680	0.726
Food Stores	0.589	0.559
Health Stores	0.578	0.575
Gas Stations	0.615	0.579
Clothing	0.659	0.665
Sport and Hobbies	0.579	0.569
General Merchandise	0.554	0.478
Miscellaneous Stores	0.649	0.655
Restaurants	0.874	0.849

Note: The table reports correlation coefficients between Safegraph visits and payment card transactions and expenditures across all matched zip codes after trimming the top and bottom 1% of observations. The first row contains the correlation between the sum of the variables across all 11 categories.

Appendix Table A6: Card usage regression results

	(1)
	Card share of spending
2 Middle Atlantic	-0.0195
	(0.0394)
3 East North Central	0.0402
	(0.0375)
4 West North Central	0.0678
	(0.0397)
5 South Atlantic	0.0899
	(0.0380)
6 East South Central	0.0119
	(0.0436)
7 West South Central	0.0835
	(0.0422)
8 Mountain	0.132
	(0.0428)
9 Pacific	0.114
	(0.0400)
Gas	-0.0275
	(0.0189)
Restaurants	-0.138
	(0.0180)
Other	0.0306
	(0.0180)
35-75k	0.159
	(0.0195)
75-100k	0.204
	(0.0224)
>100k	0.266
	(0.0189)
Constant	0.462
	(0.0379)
Observations	4496
R^2	0.070

Note: The table reports regression results from estimation of Equation 1 using 2018 DCPC data. The dependent variable is the share of respondent spending in a NAICS group that occurs on credit and debit cards. Control variables include fixed effects for income group, Census division, and NAICS category. The baseline categories for each control variable are New England (Census division), Grocery stores (NAICS), and the 0-35K income group.

Appendix Table A7: Ratio of spending to visits

(a) 2018

	mean	sd	p10	p50	p90
All	2084.2	69599.0	411.6	863.1	1941.0
Motor Vehicles	2157.6	80755.0	276.3	773.3	2000.5
Home Furnishings	5270.0	105569.0	321.9	1455.6	4716.2
Electronics and Appliances	11381.1	128510.1	114.5	1398.6	8648.9
Building Materials	8110.0	403950.2	440.4	1391.4	3684.6
Food Stores	4179.2	108405.1	380.6	1448.4	4581.7
Health Stores	883.2	2617.2	233.0	626.7	1576.4
Gas Stations	1823.5	5293.4	497.0	1212.2	3351.2
Clothing	11023.0	266979.1	216.7	1254.3	5607.7
Sport and Hobbies	922.8	11396.4	98.7	386.5	1267.6
General Merchandise	2388.9	37163.4	194.5	662.4	3220.1
Miscellaneous Stores	805.3	8492.8	102.2	352.8	1114.9
Restaurants	1430.3	45614.6	350.9	706.6	1458.8

(b) 2019

	mean	sd	p10	p50	p90
All	1473.5	24202.1	356.6	759.6	1733.2
Motor Vehicles	1621.3	50883.1	255.6	721.7	1917.0
Home Furnishings	3472.8	43059.4	293.7	1296.8	4228.9
Electronics and Appliances	9874.0	105388.4	108.4	1406.0	8423.6
Building Materials	8151.7	438013.7	401.0	1194.7	3089.3
Food Stores	3237.9	62717.9	333.5	1224.8	4116.2
Health Stores	839.6	2163.1	219.1	581.5	1489.4
Gas Stations	1709.6	19296.0	410.9	1005.9	2823.5
Clothing	6070.3	115869.4	233.2	1165.8	4940.5
Sport and Hobbies	2624.3	109117.1	88.0	342.0	1084.2
General Merchandise	2713.3	68332.5	190.8	627.4	3002.1
Miscellaneous Stores	801.0	15225.6	92.2	320.5	984.3
Restaurants	1133.8	22566.1	306.3	638.6	1334.2

Note: The table reports summary statistics of the ratio of dollars to visits across zip codes by NAICS and year. The "All" row shows the ratio of aggregate dollars to visits across all NAICS categories.

Appendix Table A8: Weights regression results

	(1) 2018	(2) 2019
Med. income quartile=2	0.137	0.134
	(0.0106)	(0.0106)
Med. income quartile=3	0.255	0.266
	(0.0109)	(0.0108)
Med. income quartile=4	0.429	0.455
	(0.0119)	(0.0118)
Med. age quartile=2	0.0450	0.0280
	(0.0103)	(0.0102)
Med. age quartile=3	0.0738	0.0449
	(0.0109)	(0.0108)
Med. age quartile=4	0.184	0.167
	(0.0121)	(0.0119)
Pct. white quartile=2	0.123	0.0924
	(0.0108)	(0.0106)
Pct. white quartile=3	0.121	0.0772
	(0.0120)	(0.0118)
Pct. white quartile=4	0.0895	0.0406
	(0.0139)	(0.0139)
Pop. density quartile=2	-0.0898	-0.0615
	(0.0100)	(0.0101)
Pop. density quartile=3	-0.0714	-0.0294
	(0.0111)	(0.0112)
Pop. density quartile=4	-0.198	-0.111
	(0.0128)	(0.0127)
naics=442	0.672	0.609
	(0.0153)	(0.0153)
naics=443	0.837	0.821
	(0.0261)	(0.0274)
naics=444	0.523	0.435
	(0.0133)	(0.0134)
naics=445	0.629	0.543
	(0.0114)	(0.0114)
naics=446	-0.229	-0.252
	(0.0136)	(0.0137)
naics=447	0.491	0.378
	(0.0116)	(0.0116)
naics=448	0.609	0.563
	(0.0148)	(0.0148)
naics=451	-0.549	-0.654
	(0.0196)	(0.0195)
naics=452	0.254	0.205
	(0.0194)	(0.0190)
naics=453	-0.618	-0.689
	(0.0167)	(0.0161)
naics=454	0.0840	1.062
	(0.333)	(0.0486)
naics=722	-0.238	-0.280
	(0.0108)	(0.0105)

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(Table A8, continued)

	Dollars/visits 2018	Dollars/visits 2019
ALASKA	0.896	1.136
	(0.0585)	(0.0570)
ARIZONA	0.480	0.541
	(0.0354)	(0.0346)
ARKANSAS	-0.268	-0.256
	(0.0404)	(0.0411)
CALIFORNIA	0.325	0.468
	(0.0292)	(0.0284)
COLORADO	0.673	0.750
	(0.0347)	(0.0337)
CONNECTICUT	0.442	0.554
	(0.0377)	(0.0373)
DELAWARE	0.526	0.678
	(0.0528)	(0.0544)
DISTRICT OF COLUMBIA	-0.203	0.559
	(0.109)	(0.104)
FLORIDA	-0.0167	0.151
	(0.0307)	(0.0296)
GEORGIA	-0.106	-0.0527
	(0.0333)	(0.0336)
HAWAII	0.630	0.727
	(0.0598)	(0.0578)
IDAHO	0.638	0.732
	(0.0441)	(0.0434)
ILLINOIS	0.231	0.302
	(0.0321)	(0.0316)
INDIANA	0.205	0.251
	(0.0353)	(0.0352)
IOWA	0.187	0.206
	(0.0453)	(0.0458)
KANSAS	0.226	0.303
	(0.0413)	(0.0415)
KENTUCKY	0.176	0.188
	(0.0375)	(0.0366)
LOUISIANA	-0.0867	-0.0620
	(0.0392)	(0.0360)
MAINE	1.022	1.105
	(0.0424)	(0.0419)
MARYLAND	0.398	0.555
	(0.0350)	(0.0342)
MASSACHUSETTS	0.623	0.764
	(0.0328)	(0.0319)
MICHIGAN	0.176	0.273
	(0.0329)	(0.0326)
MINNESOTA	0.650	0.709
	(0.0339)	(0.0335)
MISSISSIPPI	-0.274	-0.259
	(0.0419)	(0.0440)

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(Table A8, continued)

	Dollars/visits 2018	Dollars/visits 2019
MISSOURI	0.0783	0.105
	(0.0366)	(0.0372)
MONTANA	0.765	0.898
	(0.0446)	(0.0452)
NEBRASKA	0.355	0.356
	(0.0495)	(0.0476)
NEVADA	0.368	0.457
	(0.0479)	(0.0449)
NEW HAMPSHIRE	0.890	0.969
	(0.0416)	(0.0407)
NEW JERSEY	0.473	0.575
	(0.0326)	(0.0318)
NEW MEXICO	0.546	0.653
	(0.0464)	(0.0470)
NEW YORK	0.485	0.592
	(0.0305)	(0.0298)
NORTH CAROLINA	0.0917	0.155
	(0.0318)	(0.0305)
NORTH DAKOTA	0.469	0.611
	(0.0584)	(0.0653)
OHIO	0.205	0.281
	(0.0313)	(0.0310)
OKLAHOMA	0.101	0.195
	(0.0418)	(0.0396)
OREGON	0.655	0.750
	(0.0361)	(0.0354)
PENNSYLVANIA	0.520	0.629
	(0.0301)	(0.0296)
RHODE ISLAND	0.488	0.617
	(0.0526)	(0.0513)
SOUTH CAROLINA	0.0760	0.126
	(0.0362)	(0.0374)
SOUTH DAKOTA	0.667	0.710
	(0.0611)	(0.0608)
TENNESSEE	0.0426	0.104
	(0.0336)	(0.0335)
TEXAS	-0.167	-0.0756
	(0.0298)	(0.0292)
UTAH	0.594	0.613
	(0.0426)	(0.0407)
VERMONT	0.844	0.995
	(0.0514)	(0.0499)
VIRGINIA	0.398	0.527
	(0.0324)	(0.0318)
WASHINGTON	0.614	0.717
	(0.0337)	(0.0328)
WEST VIRGINIA	0.367	0.360
	(0.0531)	(0.0504)

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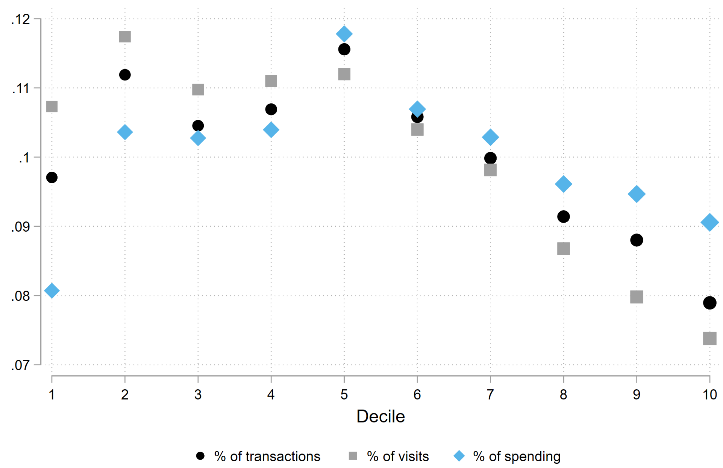
(Table A8, continued)

	Dollars/visits 2018	Dollars/visits 2019
WISCONSIN	0.472	0.544
	(0.0346)	(0.0341)
WYOMING	0.608	0.648
	(0.0629)	(0.0567)
Constant	6.348	6.200
	(0.0300)	(0.0295)
Observations	93588	92031
Pseudo R^2	0.353	0.358

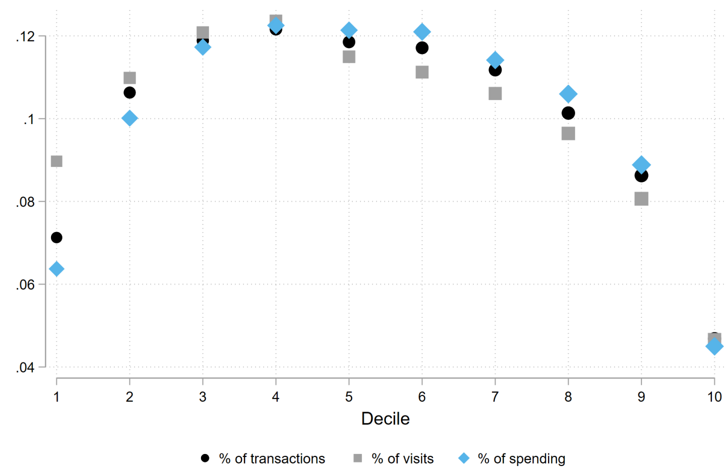
Note: The table shows the results of a Poisson regression of the ratio of dollars to visits (computed at the zip code–NAICS level) on state and NAICS fixed effects and demographic controls. The baseline categories are the first quartiles of the distributions of median income, median age, percent white, population density; NAICS 441; and the state of Alabama.

Appendix Figure A1: Share of transactions and spending by median age decile



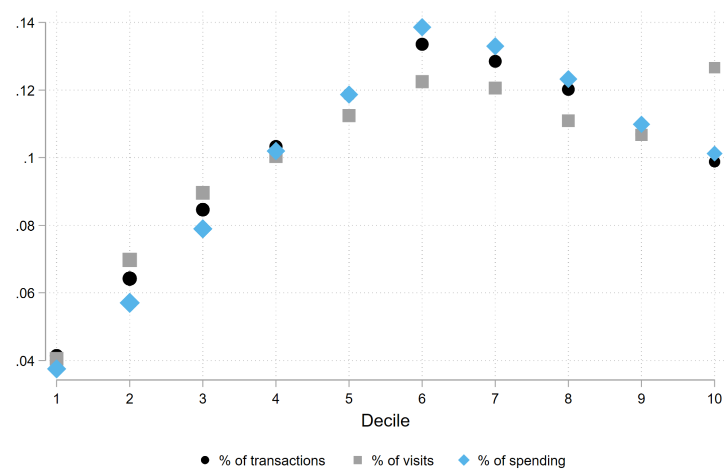
Note: The figure shows the distribution of economic activity in 2018 and 2019 across deciles of median age as measured in the payment card data (in transactions and spending) and the Safegraph data (visits). Deciles are defined based on zip code-level median age using the set of matched payment card-Safegraph data so that each decile contains 10% of the population.

Appendix Figure A2: Share of transactions and spending by deciles of white share of population



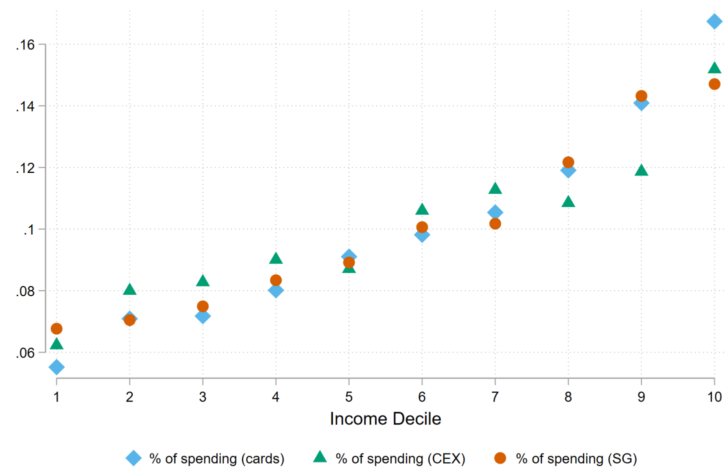
Note: The figure shows the distribution of economic activity in 2018 and 2019 across deciles based on the white share of the population as measured in the payment card data (in transactions and spending) and the Safegraph data (visits). Deciles are defined based on zip code-level share of the population that is non-Hispanic white using the set of matched payment card-Safegraph data so that each decile contains 10% of the population.

Appendix Figure A3: Share of transactions and spending by decile population density



Note: The figure shows the distribution of economic activity in 2018 and 2019 across deciles of population density as measured in the payment card data (in transactions and spending) and the Safegraph data (visits). Deciles are defined based on zip code-level population density using the set of matched payment card-Safegraph data so that each decile contains 10% of the population.

Appendix Figure A4: Share of adjusted spending by income decile



Note: The figure shows the change in the distribution of spending across income deciles after applying the adjustment for selection described in Section 3.2. The plot shows the distribution of raw spending in the payment card data (in blue), the CEX (in green), and our estimated spending computed from reweighting Safegraph visits (orange). Income deciles are defined based on zip code-level median household income using the set of matched payment card-Safegraph data so that each decile contains 10% of the population. We match the CEX data to these deciles by aggregating observations that fall in the income range of each decile and computing average spending per respondent in retail categories.

B Local multipliers

CBSA-level analysis

We replicate the CBSA-level analysis in Auerbach et al. (2020) using our measure of local spending. We first aggregate local consumption and DoD spending at the CBSA level. We then estimate the following regression:

$$\frac{ls_{2019,c} - ls_{2018,c}}{ls_{2018,c}} = \alpha + \beta \frac{DoD_{2018,c} - DoD_{2017,c}}{ls_{2018,c}} + \varepsilon_c \tag{3}$$

where $ls_{t,c}$ is estimated spending in year t and CBSA c, aggregated over the 11 NAICS that we study. We show the results in Table A9. In columns (3) and (4), we add lags of the independent variable in additional years.

Appendix Table A9: CBSA-level regression

	(1)	(2)	(3)	(4)
Δ DoD spending 2018-19			-0.00384	0.0843
			(0.00507)	(0.0786)
Δ DoD spending 2017-18	0.0301	0.168	0.104	0.193
	(0.0206)	(0.158)	(0.0332)	(0.132)
Δ DoD spending 2016-17			0.142	0.113
			(0.0519)	(0.146)
Δ DoD spending 2015-16			-0.112	0.228
			(0.0319)	(0.143)
Constant	0.169	0.146	0.169	0.143
	(0.00269)	(0.00687)	(0.00269)	(0.00728)
Weighted Regression	No	Yes	No	Yes
Observations	894	894	894	894

Note: The table shows results from estimation of Equation 3. The dependent variable is the 2018-2019 percentage change in estimated retail spending at the CBSA level. Columns (1) and (3) report results from an unweighted specification, while (2) and (4) weight observations by their 2018 level of spending.

Estimation using raw Safegraph visits

We estimate equation 2 using raw Safegraph visits at the zip code level, summed across NAICS categories. We show the results in Table A10.

Appendix Table A10: Regression using raw cell phone visits

	(1)	(2)	(3)	(4)
DoD spending within 10 miles	-0.484	-1.891	0.118	0.0983
	(0.0439)	(0.148)	(0.0377)	(0.0563)
DoD spending between 10 and 25 miles	0.00798	0.0395	0.0358	0.0409
	(0.00255)	(0.00864)	(0.00777)	(0.0209)
DoD spending between 25 and 50 miles	0.00140	0.00214	0.00210	0.00523
	(0.000329)	(0.000611)	(0.000526)	(0.00110)
DoD spending between 50 and 100 miles	0.000196	0.000149	0.0000127	0.0000363
	(0.0000434)	(0.0000664)	(0.00000805)	(0.0000244)
Constant	0.307	0.310	0.0875	0.0875
	(0.00103)	(0.00127)	(0.00277)	(0.00277)
1% Trim	Yes	Yes	No	No
Weighted Regression	No	No	Yes	Yes
IV	No	Yes	No	Yes
Observations	30,670	30,670	33,083	33,083

Note: The table shows results from estimation of Equation 2. The dependent variable is the 2018-2019 percentage change in raw cell phone visits, summed over retail NAICS categories, within a 10-mile radius of a zip code. Columns (1) and (3) report results from an OLS regression, while (2) and (4) instrument for DOD spending with a Bartik-style instrument.