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Consumption Zones

Authors Andrea Batch, Benjamin Bridgman, Abe Dunn, and Mahsa Gholizadeh*
U.S. Bureau of Economic Analysis

Contact abe.dunn@bea.gov

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Abstract Local area data are important to many economic questions, but most local area data are reported using political units, such as counties, which often do not match economic units, such as product markets. Commuting zones (CZs) group counties into local labor markets. However, CZs are not the most appropriate grouping for other economic activities. We introduce consumption zones (ConZs), groupings of counties appropriate for the analysis of household consumption. We apply the CZ methodology to payment card data, which report spending flows across U.S. counties for 15 retail and service industries. We find that different industries have different market sizes. Grocery stores have more than five times the number of ConZs as live entertainment. Industries with more frequent purchases are more local than those with infrequent purchases. We apply ConZs to measuring industry concentration. ConZs give lower concentration levels than counties, with the largest gap for infrequent purchase industries. The difference is economically important. Using concentration thresholds from the industrial organization literature, some industries are below the these thresholds with ConZs but above them for counties. We further illustrate the importance of ConZs by analyzing the proposed merger of Albertsons and Kroger.

Keywords Consumption Zones (ConZs), Consumption, Geographic Markets, Concentration, Card Data

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1. Introduction

Local area data are important to many economic questions. However, data are often reported by political units. Counties, the finest available units for many data sources, often do not match economic questions. A lot of economic activity, such as commuting or consumption (Dunn & Gholizadeh 2023), crosses county lines. Furthermore, counties are not comparable across areas, since their size varies by state and historical conditions.

Data analysts have long understood this problem, and alternative clusters of counties have been created. A prominent one in wide use are Commuting Zones (CZ). They were introduced by Tolbert & Sizer (1987) and recently re-examined by Foote, Kutzbach & Vilhuber (2021) to delineate counties across the United States into geographic local labor market. CZs are clusters of counties formed using commuting flows. CZs have an advantage over other geographic markets such as Core-Based Statistical Areas (CBSAs), since they span all geographic areas in the United States, including rural counties. CZs have been applied in numerous papers, including recent works such as Autor, Dorn & Hanson (2013), Chetty, Hendren, Kline & Saez (2014), Acemoglu, Akcigit & Kerr (2016), and Autor, Dorn, Hanson & Majlesi (2020).

As useful as CZs have been for labor market questions, they may not be appropriate for all economic applications. Retail sales and services consumption may have different geographic markets than labor markets. Comparing the distribution of workplaces (offices and factories) and retail outlets indicates that they are likely to create different geographic flows. A recent controversy that requires accurate geographic areas is measuring the concentration of retail and service outlets. Afonso & Venâncio (2016) argue that CZs are not relevant for analysis of spending. However, without a better set of clusters, analysts must either rely on non-economic units (Rossi-Hansberg, Sarte & Trachter (2020) use ZIP Codes as baseline) or commuting zones (Smith & Ocampo 2021).

We introduce "Consumption Zones" (ConZs) to identify geographic areas suitable for analyzing consumption. We use county sales flow data constructed by Dunn & Gholizadeh (2023) based on card transaction data from Fiserv, a major card transaction intermediary that includes all types of card transactions, including debit, credit, and gift card transactions. We apply the Foote et al. (2021) clustering methodology used to identify CZs to our sales flow data for 15 industries requiring physical presence, as well as other groupings such as aggregate consumption. Relative to all other geographic groupings, we argue that the ConZs are preferable for analyzing questions related to consumption, as they are formed based on actual consumption patterns. We then demonstrate why differences in groupings matter by comparing market concentration measures using ConZs to other geographies that have been used in the literature.

Consumption markets differ from labor markets. Consumption is more local than labor markets on average. Aggregate ConZs, those calculated using all consumption flows together, include fewer counties than CZs on average. We find 1,235 ConZs compared to 810 CZs. (There are 3,128 counties.) The geography of consumption flows do not necessarily follow commuting flows. ConZs are not just subsets of CZs. For example, Arlington County, VA, is part of the CZ centered on Washington, DC, but not part of its aggregate ConZ. Moreover, travelling for consumption is arguably as important, if not more important, than traveling to work, as individuals spend more time traveling for purchasing goods and services than they spend traveling to and from work.[1]

Different industries within consumption zones have very different markets. The most local industry is food and beverage stores, with 1,862 ConZs. The least local industry, live entertainment, has a sixth as many ConZs at 322. Even industries that serve similar roles can have very different geographies. While food and beverage stores are very local, restaurants are much less local, with 997 ConZs. An important ingredient is the frequency of purchase. Industries with more frequent purchases, as documented in Agarwal, Jensen & Monte (2020), tend to be more local. Among retailers, non-durable goods stores tend to have localized markets, while durable goods stores draw from wide areas.

To examine the economic importance of using the appropriate clusters, we apply ConZs to the measurement of concentration using data spanning from 1990 to 2019. We use ConZs to calculate concentration measures for 15 industries. Concentration is generally lower with ConZs compared to county measures. The gaps are largest for infrequent purchases, and the differences can be economically meaningful. We find cases where county level concentration would be considered high based on antitrust thresholds, but below the threshold when we use ConZs. Live entertainment and recreation services have levels of concentration at the county level that are considered high based on antitrust thresholds, while concentrations using ConZs are not. Those industries have relatively few outlets but draw from a wide geographic area, so more local units will tend to overstate concentration.

We find that for most industries and geographic markets, concentration was low in 1990 and remained low in 2019. Any move to highly concentrated markets is driven by a few industries. Gas stations and general merchandise stores are the only industry where most ConZs were highly concentrated in 2019. In three others (food stores, general merchandise, and building materials), there is a clear increase in the number of highly concentrated markets. However, a majority of those markets are still not highly concentrated. Most of the industries had low levels of concentration throughout the period from 1990 to 2019 with little change in concentration.

[1] According to 2015 estimates from the American Time Use Survey the average travel related to work was about 15 minutes a day, while travelling for purchasing goods, services, and food accounted for around 30 minutes per day.

To provide an illustration, we we apply our concentration measures to the proposed merger of Albertsons and Krogers announced in October of 2022. Kroger and Albertsons are two of the largest grocery conglomerates in the United States. Combined, the stores business would have around $200 billion in revenues and around 5,000 stores (Creswell (2023)). We demonstrate how using the ConZ for the food and beverage market may be applied to measure concentration changes and how those changes might differ using alternative geographic metrics (e.g., state or county). Using ConZs we find that around 11 percent of the combined firms revenues fall in geographic markets where the concentration change is high. We also show how using political boundaries, such as states or counties, can either understate or overstate the level of concentration in different markets, relative to ConZs. While more analysis is clearly necessary for a complete antitrust assessment, the application illustrates how ConZs may be a useful starting point for measuring local consumption.

This paper contributes to a wide variety of literatures that use geographic consumption markets. These include geographic markets for purposes of measuring market power and concentration (Rossi-Hansberg et al. 2020) and (Smith & Ocampo 2021), consumer market research, local area price measurement (Handbury (2021) and Handbury & Weinstein (2015)), "home bias" measures in consumer expenditure (Dupor, Karabarbounis, Kudlyak & Mehkari 2018) as well as geographic linkages in networks (Acemoglu et al. 2016). ConZs are well-suited to analyzing local economic shocks to income or wealth, such as the recent work of Mian, Rao & Sufi (2013), Mian & Sufi (2014), Guren, McKay, Nakamura & Steinsson (2020), and Chodorow-Reich, Nenov & Simsek (2021) analyzing the effects of wealth changes on spending and employment in the non-tradable sector. Each of these papers use alternative methods for addressing the limitations of the geographic market. For instance, Guren et al. (2020) use the CBSA; Mian et al. (2013) and Mian & Sufi (2014) use the county; Chodorow-Reich et al. (2021) use both the county and commuting zones; Handbury (2021) uses the CBSA; and Handbury & Weinstein (2015) uses consolidated MSAs.[2] However, conceptually these papers care about the geographic market for consumption, so the ConZ may be the conceptually more appropriate economic geography to consider. Finally, BEA and other statistical agencies provide a variety of regional and local economic statistics. ConZs contribute to improving these regional statistics by offering a new and useful metric for grouping local area statistics related to consumption.

The paper proceeds as follows. We begin by presenting how we estimate ConZs. We document the consumption data and clustering methodology we use. We then present our consumption zone estimates. Finally, we apply our estimates to concentration measures, including the proposed merger of Albertsons and Kroger.

[2] In contrast, Dunn & Gholizadeh (2023) use spending flows directly in their analysis of the Great Recession, so that the firm revenues in counties are affected by the housing wealth changes based on where their customers reside.

2. Estimating Consumption Zones

This section presents how we calculate ConZs. We document the data that we use and the method for clustering that creates ConZs.

2.1. Data

Our primary data source used to produce spending flows that enter the clustering algorithm is from Fiserv, which has information on where individuals live and the location of firms where they consume. Fiserv is one of the largest card transaction intermediaries in the United States, with millions of merchants included in the data. Once a merchant receives Fiserv services, then all card transactions go through their systems, including credit, debit, and prepaid gift cards and includes all types of card merchants (e.g., Visa, MasterCard, Discover, and others).[3] The unit of observation is a single transaction at a firm. However, the data that we see are at the county level. Fiserv worked with Palantir, a software company specializing in analysis of big data, to aggregate and anonymize the transaction data to the county level.

To obtain a coherent set of flows, these raw data need to be processed. The raw data do not fully describe consumption flows due to suppressions to protect privacy and the fact that card transactions are an incomplete picture of consumption expenditures for some sectors (e.g., health care). We use the procedures applied by (Dunn & Gholizadeh 2023), which we summarize below.

First, we must determine a card-holder's home county. The card-holder's home location is estimated based on the transaction history of the consumer using information on all transactions across all industries available in the Fiserv database for the specific card.[4] The data we analyze in this study include aggregate information by county and three-digit North American Industry Classification System (NAICS) code. The 15 NAICS industries that we study account for 79 percent of personal consumption spending, after excluding housing, health care, and financial services.[5] The available data includes county-NAICS combination containing an estimate of the share of revenues that go to consumers residing across counties within the U.S. and also information about cards from foreign countries. For the purpose of this analysis, we have excluded foreign flows.

[3]Other electronic card transactions are also included, such as electronic benefit transfer (EBT) used to process Supplemental Nutrition Assistance Program (SNAP) benefits.

[4]As a check on the home location algorithm, we are also provided with county-level data based on a subset of cards that have a known home-location ZIP Code.

[5]These industries account for 64 percent of personal consumption spending if only housing and financial services are excluded (see Dunn & Gholizadeh (2023)).

The data includes some transactions from e-commerce (primarily captured in NAICS category 454 for non-store retailers), but the coverage for this category is relatively poor, so we excluded e-commerce firms.[6]

For every county-industry combination, the data contain an estimate of the share of revenues for establishments in that county coming from consumers residing in each county in the United States. For instance, these data include information on the share of accommodation revenues (NAICS 721) in Clark County, Nevada (i.e., Las Vegas) coming from Orange County, California. The total shares across all areas add up to one.

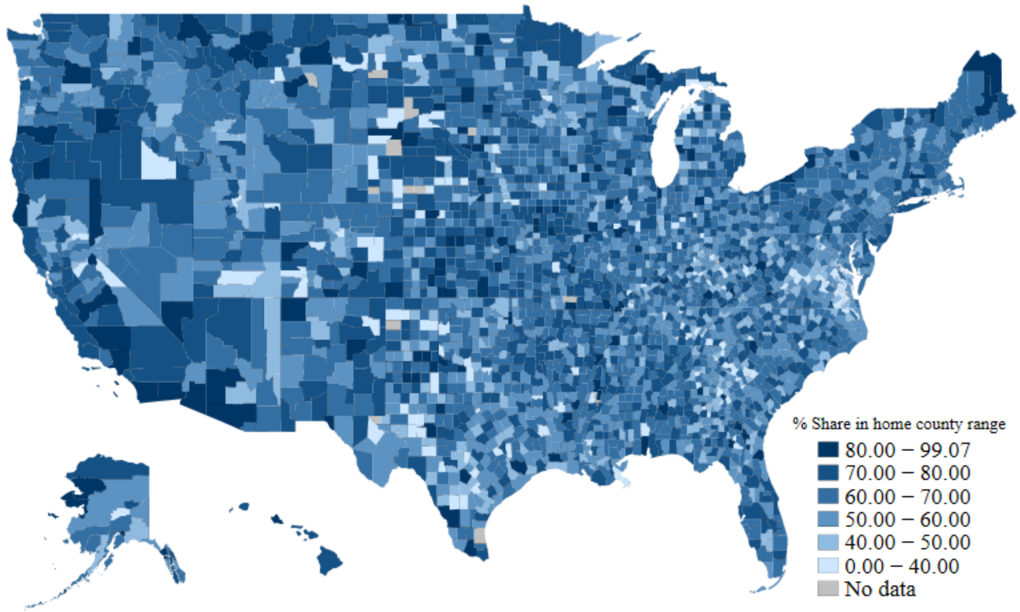
County-to-county flows in Fiserv data can be suppressed in some cases to protect anonymity of merchants and consumers (around 15 percent of revenues). The suppression rule applied has two criteria: (1) no series has observation within a given NAICS code and geography containing fewer than 10 merchants, and (2) across the series, no merchant makes up more than 20 percent of the transaction volume. This is more common in areas where revenues for the industry for a particular county are small.

To generate transaction flows in nearly all areas where final goods are sold across the United States we impute the missing flows by applying a variety of flexible models based on observable transactions in the database. Specifically, for a county missing consumption flows for an industry, the observed consumption flows for other industries in the county are used for prediction, combined with information on distances traveled, revenues estimated based on the economic census, and other covariates to impute remaining spending flows (see (Dunn & Gholizadeh 2023) for additional detail).

On average we find that around 68 percent of expenditures take place in the same county that individuals reside and that about 87 percent of spending occurs within a 100 mile radius of the home county. While these statistics show that spending typically occurs where individuals reside, spending outside the home county still makes up a substantial share of total spending. There is significant variation in how local consumption differs across industries. Some industries are very local, like food stores and general merchandise. Others have very little local spending, like accommodation and live entertainment, where the vast majority of expenditures occur outside the home county. These differences can be observed in detail in Table 1, which shows how the share of spending at home varies across industries. Moreover, the level of spending in the home county varies depending on the local geography, as shown in Figure 1, which shows considerable variation in the share spent in the home county across the United States. These results suggest that geographic consumption patterns differ a great deal across industries, so consumption clusters should also differ. We will return to this point below.

[6] The data on e-commerce is out of the scope of this study which focuses on the travel to consume feature of the data.

Figure 1. Share of Consumer Spending in Home Location



Notes: This figure shows the share of spending in the consumer's home location based on the 15 select industries in our analysis. Darker shades indicate more spending in the home county of the consumer. Figure and data based on (Dunn & Gholizadeh 2023).

Following Foote et al. (2021) we also use data from 1990 Census County-to-County Commuting Flows referred to as Journey to Work (JTW) data. The data source is from the long form of the decennial Census. The data contain the county of residence of the employee and the county of the employer where the employee commutes.[7]

[7]https://www.census.gov/data/datasets/1990/demo/commuting/worker-flow.html

Table 1. Distribution of Spending Share From Consumers that Reside in the Same County as the Firm

	Median	10th	25th	75th	90th
Accommodation (NAICS 721)	0.152	0.058	0.104	0.215	0.312
Ambulatory Health Care Services (NAICS 621)	0.760	0.563	0.664	0.873	0.939
Amusement, Gambling, and Recreation Industries (NAICS 713)	0.509	0.233	0.353	0.665	0.788
Building Material and Garden Equipment and Supplies Dealers (NAICS 444)	0.824	0.639	0.738	0.893	0.941
Clothing and Clothing Accessories Stores (NAICS 448)	0.590	0.359	0.482	0.703	0.852
Food Services and Drinking Places (NAICS 722)	0.633	0.409	0.527	0.712	0.769
Food and Beverage Stores (NAICS 445)	0.829	0.657	0.760	0.880	0.909
Furniture and Home Furnishings Stores (NAICS 442)	0.591	0.353	0.470	0.726	0.897
Gasoline Stations (NAICS 447)	0.651	0.442	0.545	0.736	0.795
General Merchandise Stores (NAICS 452)	0.811	0.646	0.736	0.867	0.918
Miscellaneous Store Retailers (NAICS 453)	0.617	0.353	0.492	0.723	0.820
Performing Arts, Spectator Sports, and Related Industries (NAICS 711)	0.315	0.098	0.186	0.437	0.578
Personal and Laundry Services (NAICS 812)	0.762	0.556	0.671	0.840	0.916
Repair and Maintenance (NAICS 811)	0.735	0.507	0.629	0.833	0.909
Sporting Goods, Hobby, Book, and Music Stores (NAICS 451)	0.665	0.444	0.557	0.798	0.937

Notes: These estimates are based on data discussed in greater detail in (Dunn & Gholizadeh 2023). Each row reports the share of merchant revenues that are to customers that reside in the same location as the merchant. The table reports the distribution of that share across all counties in the data. For example, for food services and drinking places (722) the median county receives 63 percent of their spending from consumers that reside in the same county as the firm.

3. Methods

To cluster the data, we use the methodology used to calculate CZs. Since CZs have been widely used in labor market applications, it is natural to use the same methodology for consumption data. Therefore, the only difference between ConZs and CZs in our analysis is the underlying data. We do not have to worry about methodological differences generating the differences in clusters.

The CZ was introduced by Tolbert & Sizer (1987) (TS) to group counties into areas where most commuting occurs within its borders. This was a significant improvement over existing geographies. It was based on economically meaningful data, while political boundaries are likely not. They also include all areas, including non-MSA counties. They are easy to apply, since many data sources are reported at the county level.

We use Foote et al. (2021) (FKV) version of the CZ methodology. As TS developed the CZ methodology in the 1980s, they were constrained by computational requirements, so to reduce computation burden, the TS methodology imposed certain groupings manually. In contrast, FKV exploit the improvements in computational speed over the past several decades and develop a methodology that requires more computation, but less judgment. To be as transparent as possible, we use the FKV method.

3.1. Agglomerative Clustering

We begin with the intuition for the method and then present the details.

The clustering is a simple iterative process. It starts with initial clustering, where each county is a cluster. It then calculates a matrix of how "close" each cluster is to all other clusters and joins two "closest" clusters into new cluster. This process is repeated until all clusters are above a predetermined distance ("height"). The one judgement FKV requires is the selection of the cutoff threshold. We discuss this selection below.

The measure of distance is a dissimilarity matrix D, which represents the relative distance between all pairs of counties.

$$D_{i,j} = 1 - \frac{f_{i,j} + f_{j,i}}{min(Rev_i, Rev_j)}, \tag{1}$$

where $D_{i,j}$ is the dissimilarity of county i from county j, $f_{i,j}$ represents the flow of spending from households in county i to firms in county j, and $f_{j,i}$ represents the flow of spending from households to firms in the opposite direction. Rev_i represents the revenues from firms in county i, while Rev_j

represents the revenue of firms in county j. Normalizing flows with the minimum revenues of a pair upweights the association of outlying areas with metropolitan cores. Notice that the equation 1 suggests that the dissimilarity is symmetric, so $D_{i,j} = D_{j,i}$. The identical matrix is applied to the construction of commuting zones, except counts of people are used in the numerator and denominator, rather than dollar values.[8] In Appendix Section A.2.1, we show that this matrix actually relates to a common measure of similarity in economics, the cross-price elasticity. Specifically, we show how the cross-price elasticity of a simple and commonly applied theoretical model is approximated by the dissimilarity matrix.

After the dissimilarty matrix is constructed, it is used as an input into the clustering method. The clustering method assigns interrelated items, or items with similar features, into groups. (Tolbert & Sizer 1996) and (Foote et al. 2021) use a hierarchical clustering method that applies a dissimilarity matrix. Given the matrix in Equation 1, we apply an agglomerative hierarchical clustering algorithm to each pair of clusters, starting with each individual county as its own cluster, C_L, C_K, such that

$$D_{K,L} = \frac{1}{N_K \cdot N_L} \sum_{i \in C_K} \sum_{j \in C_L} D_{i,j}. \tag{2}$$

N_K and N_L are the number of counties in clusters K and L, respectively. $\sum_{i \in C_K} \sum_{j \in C_L} D_{i,j}$ is the element-wise sum of the distance matrices for each county i in cluster C_K with each county j in cluster C_L.

The clustering starts with every county becoming its own cluster. Next, the lowest value $D_{i,j}$ in the dissimilarity matrix is combined with the first county in the cluster. It then recalculates the dissimilarity values between the new cluster and all the other clusters. The process continues until all nodes are clustered. Then the process may be stopped by choosing a maximum "cutoff" threshold, H, such that if $D_{K,L} > H$, then K and L do not merge.

Counties are then grouped together in a new, larger cluster based on having the smallest average distance; this agglomerative grouping ends only when all counties are clustered, or when a cutoff defined by the researcher is reached.

Selecting the cutoff value requires balancing two competing forces. If the value is too low, the clusters are not distinct from each other. If it is set too high, you may need to add very distant counties with little activity to achieve the threshold.

[8] Specifically, the distance function for commuting data is $D_{i,j} = 1 - \frac{e_{i,j} + e_{j,i}}{min(ResPop_i, ResPop_j)}$ where $e_{i,j}$ is the number of commuters from county i to firms in county j, $e_{j,i}$ is the number of commuters from county j to firms in county i, and $ResPop_i$ and $ResPop_j$ are the residents in counties i and j, respectively.

At extremely high values, the algorithm only stops when all counties are in a single cluster. Both extremes fall short of our goal to define distinct consumption markets.

In our application, the sparsely populated rural counties are a challenge. If the threshold is too high, the algorithm creates a huge cluster there, or a "greedy cluster." In particular, the value FKV use to replicate TS (0.9365) generates greedy clusters for several industries when applied to our consumption data.[9] Moreover, it is not clear that a threshold for CZs is appropriate to apply for measuring consumption.

For selecting a reasonable cutoff for ConZs, we consider both conceptual and practical issues. Conceptually, employment and consumption are distinct activities. The goal of the CZ is to capture a labor market activity. Because employment has a large effect on income, individuals may be willing to travel far within a geographic area for better job opportunities. In contrast, individual consumption items are a small share of an individual budget, so they are less likely to adjust travel substantially as prices for individual consumption items adjust. In other words, we expect individuals may be more elastic for employment opportunities than for consumption. This is important, because we want to find geographic areas where individuals are unlikely to leave for the associated activity. This intuition suggests that the area of the CZ should be larger than for the ConZ, all else equal.[10]

Practically, we select the cutoff so that the land area covered by the ConZ is consistent with external evidence of how far individuals travel to consume and the time spent traveling for purchases. In choosing the cutoff we attempt to capture a large majority of consumers, so that relatively few consumers would leave the area to consume. Essentially, we find that the land area of ConZs using a threshold of 0.9365 is substantially larger than the area we might expect consumers to reasonably travel to consume. A slight adjustment, reducing H^* to 0.90, produces clusters with land areas that match reasonably well with how far individuals typically travel. Moreover, it provides us a high cutoff that does not generate a greedy cluster for local industries. A more detailed discussion is provided in Appendix Section A.2.2.

We calculate CZs using a threshold of 0.9365 and calculate ConZs using a threshold of 0.90. As we use the same threshold for all of the ConZs, the differences we observe in the ConZ clusters is driven by the flows in the data, rather than the cutoff that we have selected. For CZs we find 810 clusters, matching results of FKV when the threshold of 0.9365 is applied in their analysis.[11] The Appendix Table A2 shows the sensitivity of the number of clusters to the selected threshold.

[9] Specifically, we get a greedy cluster for many industries, including some local industries, when we apply the 0.9365 cutoff used in an earlier version of the FKV paper for constructing CZs. There is some sensitivity to the selected cutoff that is discussed in greater detail in FKV.

[10] As mentioned previously, we show that the dissimilarity formula is actually related to a cross-price elasticity based on a simple model of consumption across geographies. Details are provided in the Appendix Section A.2.1.

[11] This is based on an earlier version of the FKV paper, where they tested the CZ for a variety of cutoff values. The official number of CZs from ERS for 1990 shows 741 CZs.

4. Consumption Zones

This section presents ConZs for aggregate consumption and the 15 component industries. We document differences between ConZs and CZs and across ConZs by industry.

A simple metric for comparing the different clusters is the count reported in Table 2. A higher number of clusters indicates that markets are smaller on average. Aggregate ConZs are more local than CZs, with 1,235 clusters, compared to 810 for CZs. Within the included consumption industries, there are wide differences in the geographic markets.

The number of clusters is inversely related to both the population and land area covered by the different zones, as shown in Table 2. As the number of zones is greater, the average land area and population are smaller. ConZs for grocery stores have the smallest average area and population, while the land area and population of the CZ is nearly double.

While in some cases the number of ConZs appears similar to CZs, the geographies of the ConZs and CZs are distinct. The last two columns report simple summary statistics that compare the ConZs to CZs. The first of the two columns reports the share of ConZs crossed by CZs (i.e., the share of ConZs that contain more than one CZ). Even though ambulatory care has a similar number of ConZs to the number of CZs, we find that about 50 percent of the ConZs contain two or more CZs, suggesting that it is common for these zones to be different. The last column measures the share of CZs that are crossed by ConZs. The contrast across the two columns is particularly interesting for the case of food and beverage stores, where 76 percent of the CZs are crossed by ConZs, but only 12 percent of the ConZs are crossed by a CZ. The reason for this difference is the the ConZs for food and beverage stores are often contained within a CZ.

Why are ConZs so different? While it is out of scope of this paper to fully specify the forces that generate ConZs, we observe some regularities. Industries with smaller geographic coverage tend to be those identified by Agarwal et al. (2020) as having more frequent purchases. Durable-goods stores have broader markets than non-durable-goods stores.

Table 2. Consumption Zone Counts by Industry

Industry	Num. of Zones	Land Area (Sq. Miles) Mean	Population Mean	Share ConZ Crossed by CZ	Share CZ Crossed by ConZ
Furniture and Home Furnishings Stores	570	6,178	563,784	0.553	0.51
Building Material and Garden Equipment	1,194	2,949	269,143	0.291	0.591
Food and Beverage Stores	1,862	1,891	172,587	0.118	0.764
Gasoline Stations	972	3,623	330,614	0.462	0.579
Clothing and Clothing Accessories Stores	567	6,211	566,767	0.672	0.531
Sporting Goods, Hobby, and Book Stores	554	6,357	580,067	0.634	0.546
General Merchandise Stores	1,198	2,940	268,245	0.324	0.627
Miscellaneous Store Retailers	900	3,913	357,063	0.511	0.556
Ambulatory Health Care Services	800	4,402	401,696	0.512	0.52
Performing Arts, Spectator Sports, etc.	322	10,937	998,003	0.568	0.658
Amusement, Gambling, and Rec. Ind.	530	6,644	606,334	0.545	0.504
Accommodation	383	9,195	839,052	0.493	0.568
Food Services and Drinking Places	997	3,532	322,324	0.42	0.57
Repair and Maintenance	1,009	3,490	318,491	0.386	0.557
Personal and Laundry Services	955	3,687	336,499	0.464	0.556
All Included Industries	1,235	2,851	260,208	0.265	0.584
Commuting Zone	810	4,348	396,737	0	0

Notes: This table reports the number of consumption zones for each industry. The last two rows report the aggregate ConZ count and a commuting zone count. The columns provide descriptive statistics for each cluster, including the mean land area in square miles and mean population. The last two columns provide comparisons with CZs. The first of the last two columns is the share of ConZs crossed by a CZ (i.e., more than one CZ within the ConZ) and the share of CZ crossed by a ConZ (i.e., more than one ConZ within the CZ). All ConZs are calculated using the threshold $H^* = 0.9$.

Figure 2 presents the cluster sets which we focus on in the greatest detail in this paper, while similar maps for the remaining industries are reported in Appendix Figure 3. The 1990 CZs (Figure 2a) are our baseline for comparison.

The aggregate CZs have a fair amount of overlap with the aggregate consumption zone clusters (Figure 2b). However, the geography of consumption flows do not necessarily follow commuting flows. Aggregate ConZs are not just subsets of CZs. For example, Arlington County, VA, is part of the CZ centered on Washington, DC, but not part of its aggregate ConZ. This is not surprising, as the distribution of stores may be very different than the distribution of workplaces. For example, central business districts typically have many offices, but few grocery stores. Further, transportation that works well for commuting, like subways, may be less useful for shopping for perishable or large items.

ConZs for the food and beverage industry (NAICS 445) are highly local and related to aggregate ConZ,

Figure 2. Clusters of counties for the contiguous United States.
a) 1990 Census JTW Commuting Zones; b) Consumption Zones (ConZs), all industries; c) ConZs, NAICS 445 (Food and Beverage Stores); d) ConZs, NAICS 721 (Accommodations); e) ConZs, Clothing Stores (NAICS 448); and f) ConZs, NAICS 722 (Food Services and Drinking Places). The distinct colors in each map represent a unique ConZ that may include either one or multiple counties. The same color may be used more than once and represent a distinct cluster if the color does not appear contiguously.

as well as other industries related to the sales of goods (e.g., clothing stores), and of services related to health care (NAICS 621) or to repair and maintenance (NAICS 811). The industries of performing arts and spectator sports (NAICS 711), accommodations (NAICS 721), and amusement (NAICS 713) are quite spatially dissimilar to all other industries.

Tourist-related industries such as accommodations (NAICS 721) have "greedy" clusters, with more than 100 counties in some groupings. This is unsurprising and somewhat unavoidable, as the economic activity of some industries may not necessarily be tied to a local geographic area. These mostly rural areas may be competing, generally, for consumers traveling long distances often crossing rural markets. We find three greedy clusters for accommodations that have a combined 1,688 counties, which take up a very large geographic area. However, the economic activity is relatively small, with the these counties accounting for just 26 percent of the population. Some other industries also show evidence of greedy clusters in particular geographies including Performing Arts (NAICS 711), Amusement (NAICS 713), Sporting Goods, Hobby and Bookstore (NAICS 451) and Furniture and Home Furnishings (NAICS 442). These areas can be seen in the maps shown in appendix Figure 3. Similar to accommodations, these are all industries that either attract tourists from broader geographic markets or sell infrequently purchased durable goods, and may not have as strong a connection to local consumption, but are competing more broadly for consumers across a wider geography. As we use a fixed cutoff of 0.90 for all ConZs, these areas are created based on patterns in the data, not the selected cutoff.

5. Application: Concentration Measures

Market concentration has been a significant area of inquiry recently. A strand of this literature has sought to document trends in concentration over time. An important issue for retail stores and many services is that they are consumed locally, so it is necessary to determine the relevant geographic market.

We investigate the importance of selecting markets extent by calculating Herfindahl–Hirschman Indexes (HHIs) for different clusters. This is a common measure of market concentration which spans from 0 (no concentration) to 10,000 (perfect monopoly).[12]

Our source data are from the National Establishment Time Series (NETS), from Walls and Associates. These data report annual sales and employment by lines of business at unique establishment locations from 1990 to 2019. A key variable in the data is the corporate owner of each establishment location, allowing for the calculation of market shares by owner. Rossi-Hansberg et al. (2020) use these data to conduct a similar exercise but with non-economic units; ZIP Codes are their benchmark disaggregated unit. They discuss the strengths and weaknesses of this source. Importantly, these data do not have the privacy restrictions that Economic Census data have.[13]

We need a metric to compare concentration results in an *economically* meaningful way. We use the 2010 Department of Justice (DoJ) Horizonal Merger Guidelines. These provide HHI thresholds that are an input to actual regulatory activity. Our metric is: If observed levels and changes were due to a merger, would it have been allowed? Guidelines are not a rigid rule, since much more goes into competition regulation (e.g., specific features of the industries, products, and characteristics of merging firms).[14]. However, these thresholds are a policy-relevant way to distinguish whether we get economically salient differences using different market definitions.

The 2010 DoJ guidelines presume that a market with an HHI less than 1,500 is not concentrated, while those above 2,500 are presumed to be highly concentrated. Further, HHI changes of more than 200 points are presumed to reduce competition. Following Benkard, Yurukoglu & Zhang (2021) and Nocke & Whinston (2022), we classify HHIs into three zones.

[12]We apply the standard formula where $HHI_j = 10,000 \cdot (\sum_{i \in C_K} S_{i,j}^2)$ where $S_{i,j}$ is the revenue market share of firm i in geographic area j, where j is a county, cluster or state. The estimates are weighted by the total sales in the select geographic area.

[13]See the appendix for additional details regarding the NETS data.

[14]For instance, ambulatory services includes many health care services, including specialized services such as cardiologists and orthopedic doctors. However, even these two categories of physician specialties arguably belong in distinct markets (Dunn & Shapiro 2014)

A "Red Zone" is for industries with an HHI above 2,500. The "Green Zone" is HHI below 1,500. In between is a "Yellow Zone." Industries in the Green Zone are presumed competitive, and regulators are unlikely to intervene. Those in the Red Zone are presumed to be non-competitive, and regulators are the most likely to intervene.

In what follows, we examine whether ConZs give a different view of concentration than counties or states. The goal is *not* to prove whether industries are competitive or not. The connection between concentration and market power is incomplete at best; see Syverson (2019) for a discussion. Rather, we only seek to show that getting the right market extent can affect analysis in meaningful ways. The results suggest that any investigation of market power will need to account for the different geographic markets for different types of products and services. In addition, recall that e-commerce services are not considered in our analysis and have grown in importance over our period of study, which might also affect the level of competition.

Table 3 reports the cluster HHIs weighted by sales using counties, industry specific ConZ clusters, and states as the geographic areas. They are color coded to indicate whether an industry falls within a Yellow or Red Zone.

Table 3. Sales Weighted HHIs

Industry	County 1990	ConZ 1990	State 1990	County 2019	ConZ 2019	State 2019
Furniture and Home Furnishings (NAICS 442)	759	380	124	1,003	521	226
Building Material and Garden Equip. (NAICS 444)	1,069	664	160	2,471	2,009	1,463
Food and Beverage Stores (NAICS 445)	1,141	934	350	2,095	1,920	1,129
Gasoline Stations (NAICS 447)	2,323	1,830	912	3,783	3344	2,059
Clothing and Clothing Accessories (NAICS 448)	485	290	13	668	440	243
Sporting Goods, Hobby, Books, and Music (NAICS 451)	667	350	151	1,072	643	360
General Merchandise Stores(NAICS 452)	2,011	1,467	695	3,372	3,081	2,637
Miscellaneous Store Retailers (NAICS 453)	637	343	70	970	655	294
Ambulatory (NAICS 621)	494	304	66	629	431	138
Performing Arts, Spec Sports, and Related Ind. (NAICS 711)	1,761	882	399	1,683	891	559
Amusement, Gambling, and Recreation (NAICS 713)	1,619	1,067	525	1,563	1,059	493
Accommodations (NAICS 721)	1,405	833	315	1,333	864	412
Food Service and Drinking Places (NAICS 722)	276	153	30	198	117	42
Repair and Maintenance (NAICS 811)	571	379	138	571	378	88
Personal and Laundry Services (NAICS 812)	528	328	84	582	400	127

Notes: This table reports sales weighted HHIs for three geographies (county, ConZ and state) and two time periods (1990 and 2019). HHIs are computed using the standard formula reported in the text. We classify the "Red Zone" for industries with an HHI above 2,500, which are marked red. The zone between 2,500 and 1,500 is the "Yellow Zone," which is marked orange. The "Green Zone" is HHI below 1,500, which is unmarked.

There are several implications from this table. HHIs are lower for ConZs than counties. This gap is largest for infrequent purchases with wide geographic markets. For the most local industries, like food stores, the gap is small. There are few counties in a typical ConZ, so the areas are not that different. For the less local markets, the gap can be sizable, with ConZs HHIs half those of counties.

The gap is large enough to give different concentration zones for live entertainment and recreational services. ConZs are in the Green Zone, while counties are in the Yellow Zone. These are industries that draw from a wide area. In the case of live entertainment, the vast majority of purchases occur outside the home county.

In all cases, the states show considerably lower levels of concentration than ConZs. However, even at the state level, gasoline stations appear in the Yellow Zone and general merchandise stores appear in the Red Zone.

In most cases, there is no disagreement between the county and the ConZ clusters. Most industries are not concentrated, and only four industries show concentration that would get regulatory scrutiny. Only gas stations and general merchandise stores have increasing concentration levels that put them in the Red Zone. Many services have very low concentration levels that stay essentially unchanged. Food service is one that starts low and declines.

The analysis in Table 3 gives a sense of the overall concentration levels. To get a sense of distribution of concentration across markets, Table 4 reports the share of clusters that are in the red (high) and green (low) zones using industry specific ConZs. Aside from the four concentrated industries identified above, the vast majority of ConZs are in the low (green) concentration zone. Even for the concentrated overall markets, most ConZs are not in the highest level of concentration though that share has increased. Gas stations, which is firmly in the red nationally only has a third of markets in the red. The share in the green fell significantly. Only general merchandise stores have a majority of markets in the Red Zone. These results suggest that concentration has increased for a few industries, but geography is critical in understanding the growth in concentration, as areas of significant concentration growth are limited to certain geographic markets. Many geographic markets remain unconcentrated.

One important limitation of the analysis is that the product market may be more narrow than the three-digit NAICS code. For example, even if the geographic market for ambulatory services (primarily comprised of physician services) is correct it may be the case that cardiologists do not compete with orthopedics. In this case, for a more meaningful concentration measure, a different HHI would need to be constructed separately for cardiologists and orthopedics. In other words, product-level detail may also be important, as emphasized in (Smith & Ocampo 2021).[15]

[15] Another limitation that we noted earlier is the rise of e-commerce, which we do not consider in this analysis. E-commerce may introduce competition outside the considered geography, which is not reflected in our estimates.

Table 4. Share of ConZs with High/Low Concentration

Industry	High 1990	High 2019	Low 1990	Low 2019
Furniture and Home Furnishings Stores	0.03	0.03	0.95	0.93
Building Material and Garden Equipment	0.04	0.15	0.92	0.23
Food and Beverage Stores	0.03	0.23	0.86	0.46
Gasoline Stations	0.31	0.54	0.61	0.23
Clothing and Clothing Accessories Stores	0.01	0.04	0.96	0.94
Sporting Goods, Hobby, and Book Stores	0.01	0.03	0.85	0.84
General Merchandise Stores	0.11	0.49	0.39	0.02
Miscellaneous Store Retailers	0.03	0.04	0.96	0.91
Ambulatory Health Care Services	0.01	0.03	0.97	0.94
Performing Arts, Spectator Sports	0.08	0.08	0.85	0.84
Amusement, Gambling, and Recreation	0.13	0.17	0.82	0.79
Accommodation	0.05	0.08	0.91	0.83
Food Services and Drinking Places	0.01	0.00	0.99	1.00
Repair and Maintenance	0.02	0.04	0.95	0.94
Personal and Laundry Services	0.02	0.04	0.97	0.95

Notes: This table reports sales weighted averages of ConZs that report a high level of concentration (i.e., above 2,500) and low levels of concentration (i.e., below 1,500). These estimates are reported for two time periods, 1990 and 2019. For example, 36 percent of food and beverage sales are in highly concentrated markets in 2019. In contrast, only 8 percent of sales are in highly concentrated markets for furniture and home furnishing stores.

As mentioned previously, these results are not necessarily indicative of antitrust concerns, but are suggestive of recent trends in concentration. Unlike previous studies that have examined geographic markets and concentration levels (e.g., Rossi-Hansberg et al. (2020)), the geographic markets examined here are based on actual transaction flows across geographic areas, rather than political boundaries or other non-economic measures (e.g., ZIP Codes).

5.1. Hypothetical Merger in the Food and Beverage Market: Case of a Hypothetical Kroger-Albertsons Merger

The practical importance of ConZs can be seen through an illustration suggested by the proposed merger of Kroger and Albertsons. In addition to being a large merger, the food store industry has increased concentration substantially over the past several decades, as indicated in Tables 3 and 4. The USDA ERS group has also documented steady growth in concentration in this market, with the top 20 retailers accounting for 65 percent of the sales nationally in 2019.[16]

[16] https://www.ers.usda.gov/topics/food-markets-prices/retailing-wholesaling/retail-trends/

When analyzing a merger, a key question is in what locations in the U.S. are concentration levels substantial enough to warrant additional scrutiny. To answer this question, it is first necessary to determine an appropriate geographic market. Quickly identifying the geographic markets of concern may be important, so that resources can appropriately be focused on those markets where anticompetitive concerns are the greatest. Identifying too many markets of potential concern could overly burden the regulators, while identifying too few could result in a substantial reduction in competition in many markets. Many factors go into geographic definition in merger analysis, which are not captured by ConZs. However, the ConZs may provide a useful starting point in any application involving local consumption patterns, as the market boundaries are informed by actual consumer spending patterns.

In this section, we apply the criteria described in the merger guidelines to determine the particular geographic markets that may be of concern to regulators, where we apply the ConZ for food stores (NAICS 445) as the relevant geographic market. We identify three types of markets, those where we categorize the change in HHI as high, moderate, or low. Following the merger guidelines, the change in the HHI is high if the HHI is above 2,500 and the change in the HHI is more than 200. It is moderate if the HHI is above 1,500 and the HHI in the geographic market increases by more than 100. It is low if the HHI is below 1,500 or the change in the HHI is less than 100.

In the 2019 NETS data, we identify all food and beverage stores (NAICS 445), including all of the Kroger and Albertsons establishments in this category.[17] Next, using the relevant food and beverage ConZ we measure the HHI in each geographic market prior to the merger, as well as the HHI in the hypothetical scenario where Albertsons and Kroger merge into one firm. Using these estimates we can measure both the post-merger HHI as well as the change in the HHI due to the merger — the two criteria outlined in the merger guidelines.

The results of the illustrative counterfactual analysis is shown in Table 5. Based on the criteria mentioned previously, each geographic market is categorized into a low, medium or high HHI change. We then provide descriptive statistics for those markets. The first point to note is that most markets experience a low HHI change as a result of the merger. We find 1,762 clusters fall into this low category, with a total of around 2,914 counties in those clusters. The reason for the low HHI change across many geographies is that there are around 2,214 counties where neither company is present. While the vast majority of the clusters show no change in the HHI, these tend to be relatively rural areas, so the low HHI change areas account for around 54 percent of the combined revenues of the firms. We find that 101 clusters show either medium or high HHI change (61 and 40 clusters respectively). While this is a small number of clusters, it accounts for around 46 percent of the revenue share of the firms. Applying the ConZ is able to quickly flag those areas that may be of potential concern.

[17] Specifically, we use the parent company variable in the NETS data to identify all the establishments, including all the establishments of subsidiaries. Kroger owns a variety of subsidiaries that are in the data, such as Fred Meyers, Ralphs, and Dillons among others. Albertsons' major subsidiary is Safeway.

Table 5. Hypothetical Albertsons-Kroger Merger: Concentration Changes from Using Consumption Zones

Concentration Change Category	Number of Clusters	Number of Counties	Share of Combined Revenue	HHI Level Mean	Change HHI Mean
Low HHI Change	1,762	2,914	0.543	1,799	26
Medium HHI Change	60	126	0.348	1,888	544
High HHI Change	40	79	0.11	3,136	1,132

Notes: The table shows results based on a hypothetical merger between Albertsons and Kroger where the ConZ for Food and Beverage Stores (NAICS 445) is applied. The simulation is based on using 2019 NETS data and selecting all firms in the food and beverage store category. The first row shows all markets with low concentration change (i.e., either the HHI is below 1,500 or the change in HHI is less than 100). The last row shows a high concentration change, where the HHI is above 2,500 and the change in the HHI is more than 200. The middle row shows all markets that fall between this range. The first two rows show a count of the number of clusters and counties in each category. The third column shows the share of the combined firms revenue in each category based on the NETS data. The last two columns show the mean HHI post-merger level in each category and the change in the HHI.

The importance of applying the ConZs can be demonstrated by contrasting the analysis using ConZs with alternatives using political boundaries, such as states or counties. We conduct exactly the same analysis for states and counties as we did for ConZ in Table 5. We compare the results in Table 6. Specifically, in that table we categorize ConZs and their associated counties into four categories. Two categories where the concentration changes agree: (1) both the ConZ and alternative geography find a low HHI change; and (2) both the ConZ and the alternative geography find a high or medium HHI change. The other two categories are where there is disagreement in the concentration changes: (3) high or medium HHI change using ConZ, but low HHI change using the alternative geography, and (4) low HHI change using ConZ, but high or medium HHI change using the alternative.[18]

The alternative geographies agree with ConZ for many of the markets where there is a low change in HHI. This is unsurprising given that there are many areas where Kroger and Albertsons do not overlap. However, there is disagreement in what areas do have high or medium HHI changes, especially for the state geography where there is disagreement for about 30 percent of the hypothetical firm's revenue. Using the state geography, we find that about 28 percent of the firm's revenues are flagged as having a low HHI change, while the ConZs imply a high or medium HHI change. Essentially the state markets tend to be too large and overstate the level of competition in the area, not taking into account that consumers purchase near where they live. There is much more agreement when the county geography is applied, as geographic markets for grocery stores are relatively small. However, in cases where there

[18]All the comparisons are done by ConZ. If there is a single county within the ConZ that is flagged as having a high or medium HHI change, then we flag all the counties in the market as having a high or medium HHI change. We think this is appropriate, because if there is a single county within a ConZ where there is high or medium concentration, it implies that the market may be flagged for additional scrutiny.

is disagreement it tends to be in the opposite direction as the state geography. That is, for about 2.4 percent of the combined firm's revenues the county market shows a medium or high HHI change and the ConZ does not, because the consumption zone takes into account the consumer's tendency to shop across county borders, but the county definition does not.

Interestingly, for both states and counties, there are both types of disagreement. For instance, for some counties, HHI changes based on the county may be low, but using the larger ConZ geography, the HHI change may be higher. This can occur when merging parties may be competing across county lines. To provide just one example, in Churchhill County, Nevada, there is a Safeway, which is an Albertsons-owned store, and there is no other Kroger store in the county. However, across the border in Lyon County, there is a Kroger-owned store, called Grocery Outlet, and it is just a 29-minute drive between the two stores. Using the county geographic definition, there is no change in the HHI, but using the ConZ, this area is flagged as a medium HHI change because these two counties are in the same cluster.

Table 6. Hypothetical Albertsons-Kroger Merger: Alternative Geographic Markets Compared with Consumption Zones

			State Geog.		County Geog.	
	ConZ	Alternative Geog	# of Counties	Share Rev.	# of Counties	Share Rev.
Concentration Chg.	Low HHI	Low HHI	2,691	0.508	2,894	0.518
	High/Medium HHI	High/Medium HHI	114	0.176	199	0.451
	High/Medium HHI	Low HHI	91	0.281	6	0.006
	Low HHI	High/Medium HHI	223	0.034	20	0.024

Notes: This table examines how concentration changes from the hypothetical Albertstons-Kroger merger differ across alternative geographic definitions, relative to the ConZ for NAICS 445. The ConZ market is the baseline, and the alternatives we consider are the state geographic market and the county geographic market. We perform the same analysis as in Table 5, but using the alternative geographies, and flag each geographic market as having low, medium, or high changes in concentration. We then examine whether the categorization matches the categorization for ConZ, where we focus on two categorizations, low change or medium/high change in concentration. For comparison purposes, we flag the concentration change to be medium or high if any county in the ConZ is considered to be medium or high based on the alternative geographic market. For example, using county as the geographic market, if we find a single county to have medium/high concentration change, we consider all of the counties within the ConZ to have a medium/high concentration change.

The application is intended to illustrate the importance of using the appropriate geographic market. Clearly, more analysis is necessary for a complete assessment of the merger. For example, Costco and Walmart are often categorized as general merchandise stores in the NETS data, but investigators would need to understand in what markets those stores offer groceries that substitute and compete with the merging firms stores. In addition, there may be unique market features and behaviors of firms or consumers that could lead the relevant geographic market to be either larger or smaller than that implied by ConZs. More importantly, we think the ConZ offers an improved starting point for any analysis that involves local consumption, including measuring local concentration measures.

6. Conclusion

In this paper, we introduce consumption zones (ConZs), groupings of counties appropriate for the analysis of household consumption. We estimate ConZs for 15 retail and service industries in the United States. There is a wide variance in the size of markets across industries. We apply ConZs to measuring industry concentration. ConZs give lower concentration levels than counties, and the difference is economically important in some cases. Some industries are below the antitrust enforcement thresholds with ConZs but above them for counties. These differences are also shown to be important in some markets in an illustrative example looking at the hypothetical merger between Albertsons and Kroger.

Unlike all previous geographic markets considered (e.g., state, county, CBSA, MSA, CZ, etc.), the ConZs that we introduce are the first geographic markets formed on the basis of actual spending patterns of consumers. Our newly introduced ConZs provide a more appropriate geographic market, than previously available, for applications involving local household consumption. Indeed, the measurement of local consumption is relevant to a growing literature that uses measures of local consumption to test economic theories, measure shocks and analyze policy effects (e.g., Mian et al. (2013), Mian & Sufi (2014), Handbury & Weinstein (2015), Guren et al. (2020), Handbury (2021) Chodorow-Reich et al. (2021), and Guren, McKay, Nakamura & Steinsson (2021)). It is also relevant to statistical agencies, such as BEA, that aim to produce regional statistics that will be most useful to researchers, policymakers and the public. Using the appropriate geographic market is important. Using a geographic area that is too large could wash out important differences in consumption happening at more granular geographies. In contrast, using a zone that is too small could lead to significant "leakage" that may not fully capture consumption across borders. The ConZs provide geographic markets, constructed from relevant economic data, that can be used by both researchers and policy makers to study local consumption.

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A. Appendices

A.1. NETS Data

National Establishment Time Series (NETS) data is a private sector microdata source of U.S. businesses from Walls and Associates. The source data for NETS is collected by Dunn &Bradstreet that sells the data for a variety of purposes, including marketing and research. The data used in this study is both establishment-level and longitudinal with detailed information on the industry and location of each establishment, including the exact address and the associated county of each establishment. The data also have establishment-level information on revenues and employment. When direct information on employment and revenues is not observed, the data are imputed, with imputation rates of around 13–20 percent, depending on the year of study (Crane & Decker (2019)). Because of the level of disaggregation, NETS data have been used in studies interested in location aspects of firms. The data have been found comparable to the U.S. Census Bureau's County Business Patterns (CBP) data and also the U.S. Bureau of Labor Statistics' Quarterly Census of Employment and Wages by Barnatchez, Crane & Decker (2017) in terms of establishment size, industry, and geography cells. One distinction between NETS and official data sources is the inclusion of non-employer establishments (i.e., establishments with no paid employees) in the NETS data, which is one reason why this data source diverges from the official sources.[19]

The NETS data include information on enterprises' sales and employment between 1990 and 2019. Each line of business is assigned a data universal numbering system (DUNS) identifier. The data is at SIC 8 level and at specific latitudes and longitudes. Each line of business is linked to its headquarters. Since DUNS numbers are unique identifiers an establishment can be tracked for exits and entries and also when the establishment is sold from one enterprise to another or if a merger happens. Barnatchez et al. (2017) and Crane & Decker (2019) provide discussions on advantages and disadvantages of NETS data relative to Census and QCEW data. Crane & Decker (2019) find that after applying appropriate sample selection criteria, NETS and CBP are highly correlated even at the ZIP Code level. They find some discrepancies between educational establishments and in U.S. mining, construction, and manufacturing employment all of which are out of the scope of our analysis. They find NETS more limited in its value for studying business dynamics. However, those limitations don't apply to our analysis, as we are not focused on the more problematic sectors and we do not focus on the business dynamics of individual establishments.

[19]Barnatchez et al. (2017) show that excluding the imputed non-employer establishments leaves measures of local employment on NETS highly correlated with those in CBP.

In this study, we use the mapping provided on NETS to map the SIC industry codes to NAICS industry codes. We focus on the 15 three-digit NAICS industries that are important contributors to personal consumption expenditures. Table A1 contains information on the selected industries at the level of the three-digit NAICS industries. Table A1 compares the starting and ending years on NETS data set in terms of mean and standard deviation of the employment and sales data. The last column of Table A1 contains information on number of establishments in each three-digit NAICS industry. While the number of establishments in food and drinking places increased almost three folds since 1990, the number of establishments in general merchandise stores have decreased.

A.2. Discussion of Threshold Selection

This section provides further detail about how we selected the threshold for the clustering algorithm. The first subsection presents a theoretical discussion of the algorithm. We show that for areas with localized consumption, the dissimilarity metric approximates a cross-price elasticity for a commonly used demand model. The second examines the attributes of the clusters that our baseline threshold selects. We find that the clusters about the size that one would expect given auxiliary information about how far people travel to buy various goods and services.

A.2.1. Cluster Algorithm and Cross-Price Elasticity

A concept commonly used to define the substitutability of products is the cross-price elasticity. A cross-price elasticity is the percent change in quantity for a percent change in the price of a substitute product. In this section, we show that the hierarchical algorithm is related to cross-price elasticity in a simple theoretical model.

Let the utility of consumer w residing in county i and buying from firm in county j is:

$$U_i^j = -\alpha \cdot p^j + \delta_i^j + \epsilon_{i,w}^j$$

For simplicity, we consider a discrete choice model similar to (Berry 1994) assume $\epsilon_{i,w}^j$ is an idiosyncratic error that takes the type 1 extreme value distribution. We set the utility of the outside good to zero. The term α is the marginal utility of income, that for simplicity we normalize to 1.[20] The market share of consumers residing in i purchasing from county j is:

$$S_i^j = \frac{exp(-p^j + \delta_i^j)}{1 + \sum_{l \in all\, firms} exp(-p^l + \delta_i^l)}$$

[20]As we are comparing elasticities across areas and the α term is common across areas, it would drop out from the analysis.

The cross-price derivative is then:

$$\frac{\partial S_i^j}{\partial p^l} = S_i^l \cdot S_i^j$$

For expositional purposes, assume there are just three markets 1, 2, and 3 with the number of consumers being M_1, M_2, and M_3, where each consumer spends \$1. The total sales, R^j of firm j is then:

$$R^j = M_1 \cdot S_1^j + M_2 \cdot S_2^j + M_3 \cdot S_3^j$$

The cross-price derivative of R^j with respect to p^k is:

$$\frac{\partial R^j}{\partial p^k} = \cdot(M_1 \cdot S_1^j \cdot S_1^k + M_2 \cdot S_2^j \cdot S_2^k + M_3 \cdot S_3^j \cdot S_3^k)$$

To turn this into an elasticity, we divide by the market size R_j.

$$\frac{\frac{\partial R^j}{\partial p^k}}{R_j} = \frac{(M_1 \cdot S_1^j \cdot S_1^k + M_2 \cdot S_2^j \cdot S_2^k + M_3 \cdot S_3^j \cdot S_3^k)}{R^j}$$

As a specific example we can compute the cross price of R^1 with respect to p^2:

$$\frac{\frac{\partial R^1}{\partial p^2}}{R_1} = \frac{(M_1 \cdot S_1^1 \cdot S_1^2 + M_2 \cdot S_2^1 \cdot S_2^2 + M_3 \cdot S_3^1 \cdot S_3^2)}{R^1}$$

We next show that for typical values, this term approximates the dissimilarity matrix. Typically, most consumption takes place near home, so S_1^1 and S_2^2 are closer to 1, e.g., 0.9, while the cross terms like S_3^1 and S_3^2 are small, e.g., 0.1. We use a threshold value of 0.9, so our clusters will have this structure by construction.

Taking these approximations to the formula, let $S_1^1 \approx 1$ and $S_2^2 \approx 1$, indicating that most consumption takes place in the home market.[21] Moreover, if the shares away from home are small then $S_3^1 \cdot S_3^2 \approx 0$, so we can ignore the other cross-terms. Putting these values into the formula we have:

$$\frac{\frac{\partial R^1}{\partial p^2}}{R_1} = \frac{(M_1 \cdot S_1^2 + M_2 \cdot S_2^1)}{R_1} \approx \frac{f_{1,2} + f_{2,1}}{R_1},$$

In this case, the numerator is the dollar cross-flow between the two areas where $M_1 \cdot S_1^2 = f_{1,2}$ and $M_2 \cdot S_2^1 = f_{2,1}$, which matches the numerator of equation (1). The denominator is the total revenue.

[21] Note that even if the value is not exactly 1, the main point is that the cross-term between the two areas, 1 and 2 in this case, will be relatively more important than the effects between areas 1 and 3 or 2 and 3.

The cross-price is a measure of similarity, so 1 minus this value is a measure of dissimilarity. Similar arguments can be made, even if more markets are added.

In summary, to a rough approximation, the algorithm provides a grouping of areas with higher cross-price elasticities. By grouping these similar areas together, it ensures that consuming outside of the clustered area will be relatively costly.

A.2.2. Cutoff Selection for Consumption

To select a reasonable cutoff for consumption, we use external information on how far individuals travel to consume. We focus specifically on aggregate consumption and consumption to grocery stores. We consider grocery stores separately, as it is one of the larger industries and is the most local, based on the share of individuals consuming in the home county (Table 1). The goal is to look at travel times and distances observed from external data to back out a maximum geographic area covered by potential consumers that we can use as a rough check on the land area covered by the cluster.

First, we observed land area of the clusters based on different cutoff values. The mean and median land area for the clusters with different thresholds is reported in Table A2. Each column shows the mean and median land area for the select ConZs, where each column shows the value based on a different cutoff. As expected, the land area covered increases with higher cutoff levels. We then compare these values to external estimates of how far individuals tend to travel.

Using microdata, Agarwal et al. (2020) find that about 75 percent of households travel within about 10 miles for grocery shopping. The distribution of distance traveled by consumers is skewed, so to capture nearly all consumers, we multiply this distance by 2, so the maximum a consumer might travel is 20 miles. Using the formula for the area of a circle, this translates into around 1,300 square miles potentially covered by a consumer. As a second check, we can use the Fiserv data directly. Although precise distances are not possible given the data are at the county level, we can use the population centroid to calculate rough distances between areas. We find that about 85 percent of spending takes place within a 15–20-mile radius, consistent with 20 miles capturing most spending. We could obtain a similar ballpark estimate using time use data. Hamrick, Hopkins et al. (2012) find the average individual travels around 15 to 20 minutes to get to a grocery store. To obtain a broad area that covers the maximum distance covered by consumers, we could assume consumers can travel 60 miles per hour, then we again get to a maximum of a 15–20-mile radius. Comparing the roughly estimated maximum land area covered of 1,300 to Table A2, we find that the cutoff of 93.65 produces much larger land areas, with mean and median areas of 1,735 and 2,964, respectively. Cutoffs in the range of 88 to 92 produce more reasonable values of land area covered at both the mean and median levels.

Generally consumers travel more for other types of consumption, as can be seen in Table 1 and in Agarwal et al. (2020). Based on the figures reported in Agarwal et al. (2020), about 75 percent of households travel within about 14 miles for most consumption. Again, multiplying this value by 2 and using the formula for an area of a circle, we find the maximum area potentially covered by a consumer to be 2,500 square miles. We can also look at the aggregate Fiserv data where we look at the share of spending at different distances, but excluding the most tourist-heavy industries of 721, 713, and 711. We find that nearly 85 percent of spending occurs within a 30-mile radius, supporting the idea that a substantial share of consumption occurs within this distance. (A similar estimate would be found assuming individuals travel a maximum of 30 minutes at 60 miles an hour.) Comparing to the cutoff in Table A2, the land area covered by the aggregate ConZ using a cutoff of 93.65 greatly exceeds this amount, showing 5,745 square miles at the mean and 2,972 square miles at the median. Again, cutoff values in the range of 88 to 92 produce much more reasonable values.

We select a cutoff of 90, which is a central estimate where the maximum land area covered by potential consumer falls between the mean and median values for both the aggregate ConZ and for food and beverage stores.

A.3. Additional Maps

The maps of clusters not reported above are shown in Figure 3.

Figure 3. Clusters of counties for the contiguous United States, including a) ConZs, Furniture and Home Furnishings (NAICS 442); b) ConZs, Building Material and Garden (NAICS 444); c) ConZs, Gas Stations (NAICS 447); d) ConZs, Ambulatory Health Care Services (NAICS 621); e) ConZs, Sporting Goods (NAICS 451); f) ConZs, General Merchandise (NAICS 452); g) ConZs, Misc. Retail Store (NAICS 453); h) ConZs, Performing Arts and Spec. Sports (NAICS 711); i) ConZs, Amusement Ind. (NAICS 713); j) ConZs, Repair and Main. (NAICS 811); k) ConZs, Personal and Laundry Services (NAICS 812)

Table A1. NETS Data, Sales and Employment

1990					
	Emp Mean	Emp SD	Sales Mean	Sales SD	No Obs
Accommodations (NAICS 721)	24.301	121.960	1226033.573	8883190.372	81515
Ambulatory Health Care Services (NAICS 621)	8.016	55.660	501968.770	4417372.644	467041
Amusement, Gambling, and Recreation Industries (NAICS 713)	14.408	165.777	696487.933	16453233.835	8326
Building Material and Garden Equipment and Supplies Dealers (NAICS 444)	7.446	33.037	876492.388	5017271.290	114430
Clothing and Clothing Accessories Stores (NAICS 448)	5.701	29.256	416620.597	2296600.321	237091
Food Services and Drinking Places (NAICS 722)	15.064	42.386	443881.532	2432294.580	378627
Food and Beverage Stores (NAICS 445)	12.197	46.651	1380076.969	6600938.846	251010
Furniture and Home Furnishings Stores (NAICS 442)	5.539	37.042	568718.074	3945974.772	110457
Gasoline Stations (NAICS 447)	6.051	15.956	913687.699	6847746.044	92612
General Merchandise Stores (NAICS 452)	46.493	145.877	3816163.981	15138861.916	47875
Miscellaneous Store Retailers (NAICS 453)	4.279	23.770	294333.908	1915879.048	275085
Performing Arts, Spectator Sports, and Related Industries (NAICS 711)	7.720	63.542	697399.563	9086608.262	75734
Personal and Laundry Services (NAICS 812)	4.538	19.622	152710.137	1102398.545	349354
Repair and Maintenance (NAICS 811)	4.069	30.070	267719.772	3159775.766	446493
Sporting Goods, Hobby, Book, and Music Stores (NAICS 451)	4.418	16.309	305020.875	1375295.347	149462
2019					
	Emp Mean	Emp SD	Sales Mean	Sales SD	No Obs
Accommodations (NAICS 721)	19.165	91.479	1169386.250	22044996.333	171134
Ambulatory Health Care Services (NAICS 621)	7.181	38.517	668278.276	10234780.490	1522701
Amusement, Gambling, and Recreation Industries (NAICS 713)	9.595	59.894	385479.581	9942399.548	287743
Building Material and Garden Equipment and Supplies Dealers (NAICS 444)	11.473	36.171	2339673.804	10487429.339	131878
Clothing and Clothing Accessories Stores (NAICS 448)	5.905	39.652	693310.789	4850624.168	310987
Food Services and Drinking Places (NAICS 722)	14.601	47.257	485945.157	2629984.880	996355
Food and Beverage Stores (NAICS 445)	11.111	41.005	1680130.830	9504069.132	384904
Furniture and Home Furnishings Stores (NAICS 442)	5.169	20.668	735821.323	4213109.162	153670
Gasoline Stations (NAICS 447)	7.676	36.417	4113456.317	74102874.864	87302
General Merchandise Stores (NAICS 452)	36.458	98.564	7244208.458	24025335.154	83961
Miscellaneous Store Retailers (NAICS 453)	3.904	16.397	364968.629	7894034.748	432430
Performing Arts, Spectator Sports, and Related Industries (NAICS 711)	4.703	45.876	400915.454	8527195.830	211617
Personal and Laundry Services (NAICS 812)	3.350	14.032	136964.418	2668576.555	748471
Repair and Maintenance (NAICS 811)	3.762	13.644	330971.924	3983379.156	618869
Sporting Goods, Hobby, Book, and Music Stores (NAICS 451)	5.362	28.764	502544.865	3060731.194	146557

Table A2. Consumption Zone Counts by Industry

Industry	Zones				
Cutoff	88	90	92	93.65	94
Furniture and Home Furnishings Stores	713	570	466	397	379
Building Material and Garden Equipment and Supplies Dealers	1,489	1,194	792	684	649
Food and Beverage Stores	2,120	1,862	1,539	1,188	1,099
Gasoline Stations	1,325	972	576	312	279
Clothing and Clothing Accessories Stores	780	567	433	343	330
Sporting Goods, Hobby, Musical Instrument, and Book Stores	736	554	421	338	321
General Merchandise Stores	1,481	1,198	871	581	536
Miscellaneous Store Retailers	1,190	900	609	429	410
Ambulatory Health Care Services	1,129	800	563	428	405
Performing Arts, Spectator Sports, and Related Industries	420	322	255	215	207
Amusement, Gambling, and Recreation Industries	714	530	399	334	319
Accommodation	655	383	280	240	234
Food Services and Drinking Places	1,261	997	698	514	470
Repair and Maintenance	1,258	1,009	692	506	468
Personal and Laundry Services	1,288	955	611	435	412
All Included Industries	1,532	1,235	912	613	559
Commuting Zone	1,684	1,419	1,130	810	736

Notes: This table reports the number of consumption zones for each industry. The last two rows report the aggregate ConZ count and a commuting zone count. All ConZs are calculated using the threshold $H^* = 0.9$.

Table A3. Mean and Median Land Area for Aggregate Consumption Zone and Food and Beverage Consumption Zone

		Cutoff	88	90	92	93.65	94
Food & Bev. (NAICS 445)	Land Area	Median	902	1,045	1,298	1,735	1,865
	Sq. Miles	Mean	1,661	1,891	2,288	2,964	3,204
ConZ (AGG)	Land Area	Median	1,294	1,668	2,300	2,972	3,099
	Sq. Miles	Mean	2,299	2,851	3,861	5,745	6,300

Notes: This table reports the mean and median land area for the Food and Beverage industry (NAICS 445) and aggregate consumpiton. Land area is reported for different clusters, where the different clusters are generated by different cutoff values, shown in the top of the table. For example, the median land area for food and beverage stores is 1,735 square miles, when the cutoff value is 93.65, but the median land value is just 902 square miles if the cutoff value is 88.