Consumption Segregation*

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October 2021

Abstract

Combining new granular data with existing ones we shed light on consumption segregation in the United States. We find that consumption segregation remained relatively stable over the past 15 years but shows substantial heterogeneity across space, with the most segregated state (New York) being 11 times more segregated than the least segregated one (Wyoming). Consumption segregation is higher in richer, more educated, younger, larger, and less white regions. We find a pivotal role for income segregation in driving consumption segregation, and a more muted role for racial segregation. We investigate the mechanism through which income segregation translates into consumption segregation and find a role for market incompleteness and conspicuous consumption motives.

*We thank Federico Kochen for superb research assistance, our discussant Rebecca Diamond for insightful feedback, as well as seminar participants at the ASSA and SED Meetings for their helpful comments.

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1 Introduction

The United States have experienced a rapid increase in income inequality over the past decades, which has been mirrored by an increase in spatial segregation by income.[1] These trends are pressing socio-economic issues and represent a concern for policymakers and academics alike, since they shape the lives of individuals and families, and have generated substantial work aimed at understanding their drivers and consequences. While there exists abundant work on income and other forms of segregation, little is known about the segregation of consumption. This is an object of high interest for multiple reasons. First, consumption is arguably more directly related to welfare than income alone[2] and therefore studying the segregation of consumption can provide a better understanding on the segregation of welfare, both from a short-run and a long-run perspective, insofar some durable consumption goods can be passed along generations. Second, understanding the drivers of consumption segregation is important for the design and evaluation of place-based policies aimed at providing redistribution and insurance. Third, as the evidence presented in this paper suggests, by shaping the consumption baskets of individuals and households consumption segregation may generate an externality that amplifies aggregate wealth inequality.

Despite the importance of consumption segregation for welfare and ensuing policy implications, very little is known about it as the data that would enable studying it is very sparse. Against this background, in this paper we leverage highly granular new and existing data sources to characterize the patterns of consumption segregation in the United States over time and across regions and to identify the drivers. We find that consumption segregation has been stable over the past fifteen years, but uncover substantial regional heterogeneity. Specifically, richer and more educated regions show a degree of consumption segregation 3 times higher than their respective counterparts. We then investigate the drivers of consumption segregation and find an important role for income segregation as a determinant of consumption segregation. We show that this is a reflection of insurance opportunities rather than of permanent income differences and find a role for conspicuous consumption in dampening the transmission of income segregation to consumption segregation.

We use data on consumption from two sources. First, we leverage a newly built, large

[1] See Fogli and Guerrieri (2019). The rise in segregation by income moderates the segregation on the basis of race and ethnicity, which has been the be the major organizing principle of space in the Unites States until the last third of the 20^{th} century (Massey et al., 2009).

[2] For arguments along this line, see Cutler and Katz (1992), Krueger and Perri (2006), Jones and Klenow (2016), Brouillette et al. (2020), among others.

scale dataset purchased from a private company, Infutor, that covers nearly 250 million individuals, 160 million vehicles and more than 150 million properties. We use the extensive information on car and home ownership in this dataset connected to demographic information to characterize the extent of durable consumption segregation. Second, we use the Nielsen Homescan data to measure the segregation of non-service retail consumption, which we refer to as non-durable consumption throughout the paper, for brevity. Overall, the categories of consumption that the two datasets capture account for 51% of total household spending.

We begin our analysis of consumption segregation by describing patterns across space, time, consumption categories and socio-economic groups. We measure segregation using the entropy index, a number bounded between 0 and 1 that captures how representative is the distribution of consumption in a geographic unit, a PUMA in our analysis, of that in a broader region, a CBSA, a state or the country in our analysis. We find that the segregation of total consumption has been relatively stable over the past fifteen years, masking a decline in the segregation of non-durable consumption, an increase in the segregation of vehicle consumption and cyclical patterns in the segregation of housing consumption that mirror the housing boom-bust cycle. Housing consumption is the category that exhibits the highest degree of segregation. We also document substantial heterogeneity across regions: consumption is most segregated in New York, where the average PUMA is 30% less diverse than the state. Consumption in New York is approximately ten times more segregated than in Wyoming, where consumption segregation is smallest. We find that consumption segregation is higher in regions that are richer, larger, younger, and where a large share of the population has a college degree and a small share of the population is white.

We then turn to understanding what drives consumption segregation and evaluate the extent to which it reflects other dimensions of segregation, thus providing a bridge between previously studied dimensions of segregation and the segregation of welfare. We find an important role for income segregation as a determinant of consumption segregation, and a more muted but still significant role for racial segregation. We draw a similar qualitative conclusion at the level of consumption categories, but find a larger role for income segregation in explaining durable than non-durable consumption segregation.

Motivated by the finding that income segregation is the main driver of consumption segregation, we scrutinize three economic mechanisms that can shape this relationship: market incompleteness, permanent income differences and conspicuous consumption. Market incompleteness and permanent income differences can both generate a positive relationship between income and consumption segregation as they prevent consumption insurance among individuals. Instead, conspicuous consumption can dampen this effect and reduce the segregation of visible consumption goods, even in the presence of income segregation. We find that income segregation mostly affects the segregation of consumption within narrowly defined socio-economic groups, where income differences are likely transitory, leading us to conclude that market incompleteness plays the major role in explaining why income segregation translates into consumption segregation. We also find evidence of a conspicuous consumption motive, suggesting that income segregation might generate an externality through consumption, with possible consequences for wealth inequality.

Related Work. In addition to the large body of work on residential segregation (see Trounstine (2018) and the references therein), our paper mainly relates to the recent studies on consumption differences across space by Agarwal et al. (2017), Davis et al. (2017) and Diamond and Moretti (2020). The first studies the effect of consumers' willingness to travel in shaping the characteristics of industries that deliver final consumption. The second studies the role of spatial and social frictions in influencing restaurant visits within New York City using Yelp reviews. The third provides novel evidence on expenditure differences across individuals and commuting zones using credit card transactions data and connects income and consumption inequality through sorting across space. We use alternative data sources and complement these studies by studying the segregation of the main durable consumption categories, vehicles and housing, as well as that of non-service retail consumption for the entire country. We then inspect the causes and the mechanism through which the high levels of consumption segregation emerge. We also contribute to the literature by providing measures of consumption segregation at different levels of geography and over time, which can be used in empirical studies or in estimating structural models.

By emphasizing the role of income segregation as a driver of consumption segregation, our paper is also related to papers that study the relationship between income and consumption inequality over time: Krueger and Perri (2006), Blundell et al. (2008), Fisher et al. (2013), Aguiar and Bils (2015). We contribute to this literature by focusing on segregation as the geographical element of inequality, and by also studying how this traces other dimensions of residential segregation in addition to income.

Finally, our paper connects to the empirical literature on conspicuous consumption, and in particular to the work of Charles et al. (2009), who find that Black and Hispanic households devote a larger share of their spending to visible goods in an attempt to signal status.

Other papers, such as Chao and Schor (1998) and Heffetz (2011), also find evidence of conspicuous consumption in different contexts. We complement this literature by highlighting the role of space in driving conspicuous consumption, especially if in the presence of residential segregation by income.

The remainder of the paper proceeds as follows. Section 2 described the data sources used in the analysis. Section 3 documents the patterns of consumption segregation. Section 4 analyzes the drivers of consumption segregation. Section 5 investigates the channels through which income segregation translates into consumption segregation. Finally, section 6 concludes.

2 Data

Our empirical assessment of the segregation of consumption and its relationship with other dimensions of residential segregation is based on three datasets that enable us to observe income and consumption choices of individuals, their demographic characteristics and to precisely track their locations. Specifically, we analyze consumption segregation of durables such as cars and houses using the Infutor data, non-service retail consumption segregation using the Nielsen Homescan data and income segregation using data from the American Community Survey (ACS). We discuss these datasets below. We discuss the Infutor data in greater detail, as it is relatively less used, especially in the study of durable consumption, and we compare key summary statistics with counterparts from the ACS and the Bureau of Transportation Statistics (BTS) for validation.[3]

2.1 Infutor Data

We measure consumption segregation of durables, specifically housing and vehicles, using data from Infutor. This is a large scale dataset that contains longitudinal information on the vast majority of US residents. The dataset is compiled by Infutor, a private data vendor that aggregates information on individuals using multiple sources such as phone books, voter files, credit header files, public government records, property deeds, county property records, vehicle warranties, and data from vehicle repair and maintenance providers, among other sources. The data contain information of more than 250 million individuals which are linked to 160 million vehicles and more than 150 million properties. In what follows, we describe

[3] In Appendix A, we provide further detail about other components of the Infutor dataset as well as the ACS and the Nielsen Homescan dataset.

the structure of the dataset and discuss its representativeness comparing it with data from the Census, ACS and BTS data, advantages and shortcomings. Appendix A contains a more detailed description of our treatment of the data.

2.1.1 Structure of the Infutor Data

The Infutor data is organized in four linkable data files: Auto Profiles, Property Profiles, Demographic Profiles and History of Addresses. In this project we primarily use the first three files, but describe the latter one for completeness. We have access to different snapshots of this data. Starting in 2012 through 2018 we observe the data at an annual frequency. After March 2019 we observe the data at a monthly frequency. For housing, the initial available snapshot is in 2015. Although the snapshots we observe start in 2012, or 2015, ownership records and history of addresses go much further back in time. For example, we observe ownership records of vehicles starting in the 1980s, while property deeds records go back to the 1950s. The longitudinal aspect of the data enables us to observe the history of car ownership and residences and allows us to also study trends in consumption segregation, in addition to the regional dimension.

We next describe the content of the Infutor data files that is most relevant to our paper.[4]

Auto Profiles. This file contains information on car ownership of individuals that refers to the characteristics of the car, such as the car manufacturer (make), the model, the manufacturing year, etc., as well as the first 10-digits of the Vehicle Identification Number (VIN). Additionally, the data also contains the owner's address, which allows us to identify the location of the vehicle, and select demographic and economic characteristics. The file contains approximately 160 million observations in any given period (i.e. November 2012-2018 and every month of 2019). We use this data file to measure segregation of car consumption.

As we discuss in Section 3.1, we compute two measures of segregation: along dimensions that are categorical, such as the car model, and along dimensions that are continuous, such as the value of a car. To measure the value of the cars in the Infutor data, we merge it with transaction prices for all the dealer sales of new and used cars in Texas from 2012 to 2019, based on the VIN. If the VIN is not available, we infer prices using the average transaction price of a make-model-year combination.

Although we observe snapshots of the Auto Profiles starting 2012, information on ownership records of vehicles starts as early as 1980s. With additional assumptions, this allows us

[4]Figure 4 in the Appendix contains a visual summary of this section.

to study a more extended time dimension of segregation. Specifically, for years prior to the first time we observe a vehicle we set the location of the vehicle to be the zipcode of the first snapshot in which we observe it. We are confident that this does not introduce substantial noise in our measurement, as between 2012 and 2018 we found that on average only 3.3% of the vehicles in the sample changed PUMAs while only 1.1% changed states. For years prior to 2012, we impute the value of a vehicle by using a VIN-level annual depreciation rate. Appendix A contains a detailed discussion of these procedures.

Property Profiles. This file contains information on individuals' homes ranging from address and the value of the home to characteristics of the property such as the year in which the property was built, the square footage or the quality of the building. The file contains approximately 150 million observations in any given period and we restrict attention to properties that are used for residential purposes and not for business. We use this data file to measure the segregation of housing consumption.

The dimension of housing segregation we focus on is the value of the home. To that end we use property deeds data, which contain information on the date and the price at which a property was acquired by the current owner. Although we only observe snapshots of the Property Profiles starting 2015, property deeds records go further back in time, in some cases as early as the 1950s. This allows us to not only study the spatial dimension of housing segregation, but also a generous time dimension. The complication we face is that the market value of the home is only available in the period in which a home was transacted and a deed exists. We believe that it is the market and not the book value of a home that is relevant for capturing the most relevant aspects of segregation. Therefore, to infer the value of a home at a date at which the home was not transacted and a deed does not exist, we construct zipcode-level price indices based on homes that are transacted and use these to impute the value of a home in periods between two consecutive deeds. We show in Appendix A.2 that our imputation procedure generates levels and dynamics of house prices that are in line with those published by the Federal Housing Finance Agency.

Demographic Profiles. This file contains information on individuals' demographic and economic characteristics and covers approximately 250 million individuals in any given period. In addition to addresses, the file reports individuals' age, gender, ethnicity, marital status, educational attainment, number of children and estimated income, wealth and home value. We note that the Infutor data does not contain information on race. Because we think it is important to study this dimension of segregation in relation with income and consumption, we assign race probabilistically to individuals in the data using the algorithm proposed by the Census that assigns race based on surnames according to the 2010 Census Surname Table.[5] We verify the accuracy of this imputation by comparing the race distribution in the Infutor data with that in the American Community Survey.

History of Addresses. This file contains information on individuals' current address, as well as any other address within the United States at which they lived between 1990 and 2019. The dataset contains the name, the exact address and the time period during which an individual lived at that particular location. We do not use information in this file for this project, but mention it for completeness. Diamond et al. (2019) exploit the granularity of this file to study the relocation impact of rent control in San Francisco. Qian and Tan (2020) studies how new firms' entry in a location affects individuals' choices.

2.1.2 Summary Statistics and Representativeness

Naturally, a concern about the dataset is its representativeness of the US population and of more specific demographic groups. The sheer number of observations is perhaps indicative of it, but other researchers who used these data (e.g. Bernstein et al., 2018, Phillips, 2019) verified this more systematically by comparing it with Census data. Bernstein et al. (2018) find that the dataset covers 78% of the US Census estimated adult population. The data also matches well the cross-sectional distribution of population across counties. In this section, we ask two questions. First, how representative is the Infutor data of the overall US population and of the different demographic groups we are interested in studying? Second, is Infutor data suited for studying questions related to durable consumption segregation across space and over time?

Demographics. To answer the first question, in Table 1 we contrast summary statistics of several demographic groups using the Infutor data and the ACS. Column 1 of the table reports the distributions of gender, race, educational attainment, age and household income in the ACS. Column 2 reports the corresponding distributions in the Infutor data. After

[5] We used file B from https://www.census.gov/topics/population/genealogy/data/2010_surnames.html. Census reports last names that occurred more than 100 times in its collected 2010 data, and the proportion of people with each last name that belongs to each race category (White, Black, Asian / Pacific Islander, American Indian / Alaskan Native, bi / multi-racial, and Hispanic). We assigned the likelihood of belonging to each race group in the Infutor data based on individuals' last names using the Census race data. We were able to assign race probabilistically to 90.25% of the sample.

calculating the share of the population in each demographic group in each state and in each PUMA, in Columns 3 and 4 we report the cross-state and cross-PUMA correlations of these shares between the two datasets.

The top panel of Table 1 reports the results for gender. In the ACS 51% of individuals are women, very similar to the share of women in the Infutor data, which is 52%. The correlations between state- and PUMA-level gender shares between the ACS and the Infutor data are reported in Columns 3 and 4 and are equal to 0.8 and 0.59, respectively.

In the second panel the table we report the results for race. It is important to note that while race in the ACS is self-reported, in Infutor we apply an imputation procedure that assigns race probabilistically and we take that into account when reporting race shares. In the ACS data, 75% of individuals are white, 12% are Black, while the remaining 13% belong to other racial groups. In the Infutor data, the corresponding shares are 62%, 12% and 26%. We find high correlations between race shares in U.S. states and PUMAs in the two datasets, suggesting that the Infutor data accurately captures the distribution of racial groups across space. For example, the state-level correlation between the two datasets of the share of population that is white is 0.71. For Blacks and other racial groups, this correlation is 0.8 and 0.86, respectively. The racial distribution across space is important for our analysis, as we evaluate the role of racial segregation in driving consumption segregation.

In the third panel of Table 1 we report the share of the population with and without a college degree. In the ACS 29% of the population has a college degree, while in the Infutor data this share is higher, 51%. While the average shares are different, the high correlations reported in Columns 3 and 4 suggest that the Infutor data is able to capture well which U.S. states and PUMAs have the highest share of college education population.

The fourth panel of the table shows that age distribution in the Infutor data resembles closely that in the ACS, with the exception of the age group 20-29, which is under-represented in the Infutor data. This could potentially explain the previously noted high college-share in the Infutor data. If the dataset does not cover the very young, who are still in college, this would result in a low population share of the very young and a high population share of the college educated.

Lastly, the fifth panel of Table 1 reports the income distribution in the two datasets. Although income is imputed in the Infutor data, the resulting income distribution is similar to that in the ACS. Specifically, in both datasets approximately 10% of individuals earn less than $20,000 a year and it is most common for individuals to earn between $50,000 and $75,000 a year. However, we note that the Infutor data tends to under-represent individuals with low annual income, between $20,000 and $50,000, as well as the very rich, with annual income above $125,000. The correlations reported in Columns 3 and 4 are also high, suggesting that the Infutor data is able to capture the distribution of income not only nationally, but also at the level of U.S. states and PUMAs.

Table 1: Summary Statistics of Demographics and Representativeness of the Infutor Data

		Population shares		Correlation	
		ACS	Infutor	State	PUMA
Gender					
	Female	0.51	0.52	0.80	0.59
	Male	0.49	0.48	0.80	0.59
Race					
	White	0.75	0.62	0.71	0.59
	Black	0.12	0.12	0.80	0.79
	Other	0.13	0.26	0.86	0.74
Education					
	Non-college	0.71	0.49	0.70	0.87
	College degree	0.29	0.51	0.70	0.87
Age					
	20-29	0.19	0.07	-0.13	0.38
	30-39	0.19	0.17	0.25	0.65
	40-49	0.18	0.20	0.83	0.67
	50-59	0.19	0.23	0.31	0.63
	60-69	0.16	0.20	0.37	0.78
	70-80	0.10	0.13	0.72	0.90
Income (USD)					
	$<$20,000	0.11	0.10	0.79	0.85
	20,000-29,999	0.08	0.06	0.75	0.82
	30,000-39,999	0.08	0.12	0.59	0.71
	40,000-49,999	0.08	0.12	0.83	0.68
	50,000-74,999	0.18	0.27	0.85	0.71
	75,000-99,999	0.14	0.16	0.52	0.55
	100,000-124,999	0.10	0.09	0.82	0.64
	$\geq$125,000	0.22	0.08	0.95	0.89
Number of observations		249,773,525	239,077,422	0.99	0.74

Auto. To answer the second question, in Table 2 we present summary statistics on the coverage of car ownership and the age of cars in the Infutor data. We contrast this with statistics from The Bureau of Transportation Statistics. The table report the number of vehicles and the average age of a vehicle. According to the BTS, the average age of a car is 11.5 years. Cars in the Infutor dataset are, on average, 7 months older. According to the BTS, there are 254,582,694. The Infutor dataset covers 144,863,872 of them, so approximately 57% of the total number of cars in the United States. The state-level correlation between the number of vehicles reported by the BTS and those in the Infutor data is 0.54, suggesting that our data captures well the spatial distribution of vehicles, making it suitable for the study of the segregation of this component of durable consumption.

Table 2: Summary Statistics of Vehicles and Representativeness of the Infutor Data

	National level		Correlation
	BTS	Infutor	State-level
Vehicle age	11.5	12.2	
N	254,582,694	144,863,872	0.54

Properties. Also to answer the second question, in Table 3 we report summary statistics on homeownership rates, house value, house size and year of construction in the Infutor data and compare the first two with their counterpart in the ACS. Columns 1 and report the homeownership rate for the ACS and the Infutor data, respectively. In the ACS the homeownership rate is equal to 67% while in Infutor it is 62%. As columns 3 and 4 show, we also find a very high correlation between the homeownership rates at state- and PUMA-level in the two datasets, suggesting that the Infutor data captures well not only the average homeownership rate, but also regional patters of homeownership. We also find that the Infutor data captures well the value of houses. Specifically, the average value of a house is 319,000 in the ACS and 360,000 in the Infutor data. The median home is valued at 218,000 in the ACS and 222,000 in the Infutor data. Home values are also strongly correlated between the two datasets at regional level, as Columns 3 and 4 show. Lastly, even though not available in the ACS, the table also reports the average house is 1900 square feet and was built in 1974.

Table 3: Summary Statistics of Properties and Representativeness of the Infutor Data

	National level		Correlation	
	ACS	Infutor	State	PUMA
Homeownership rate	0.67	0.62	0.88	0.88
House value (USD)				
Mean	319,081	361,336	0.58	0.60
Median	218,000	221,667	0.96	0.98
Average House size (SqFt)		1900		
Year of construction		1974		
Number of observations	137,389,926	109,691,219	0.98	

2.1.3 Advantages and Disadvantages of the Infutor Data to Study Consumption

We next discuss some advantages and drawbacks in using the Infutor data to study consumption. A large literature uses the Panel Study of Income Dynamics (PSID) and the Consumer Expenditure Survey (CEX) as main data sources for consumption (Krueger and Perri, 2006, Aguiar and Hurst, 2007, Aguiar and Bils, 2015, Andreski et al., 2014, Boar, 2020, Aguiar et al., 2020). The advantage of these two datasets is that they both cover a large share of consumption expenditure. PSID covers approximately 70% of NIPA consumption and CEX covers an even larger share. At the same time, both PSID and CEX have a size of approximately 5,000 households. This undermines the feasibility of our main research exercise as sample sizes would be very small at fine levels of geography (e.g. finer than a U.S. state). The nature of our exercise requires a much larger sample size with detailed geographical coverage.

More recent studies of consumption rely on credit and debit card transactions, or personal finance management applications to infer consumption patterns (Agarwal et al., 2017, Ganong and Noel, 2019, Dolfen et al., 2019, Olafsson and Pagel, 2018, Diamond and Moretti, 2020). Relative to this, the advantage of using the Infutor data is that it allows us to accurately capture durable consumption in the form of cars and housing, items that are likely not to be paid for using credit cards.

A drawback of using the Infutor data to study consumption segregation is that it only covers durable consumption. For this reason, we supplement our analysis with the Nielsen Homescan data, which provides rich information about household purchasing patterns at various retailers such as Walmart or Whole Foods, and allows us to also study the segregation of non-durable consumption. Even though using the Nielsen Homescan data allows us to expand our coverage of consumption categories, an important drawback remains as we are not able to measure services such as restaurant meals, hair cuts, taxi rides or other leisure activities. This dimension of consumption segregation has partly been studied already by Davis et al. (2017) in the context of restaurant meals in New York City using Yelp data, as well as theoretically by Couture et al. (2019), so we view our work as complementary. Overall, the categories of consumption we capture in the Infutor and Nielsen datasets correspond to 51% of total household spending.

2.2 Nielsen Homescan Data

Our data source on non-durable consumption is the Nielsen Homescan Data from the Kilts Marketing Data Center at the University of Chicago Booth School of Business. These data consist on a longitudinal panel of approximately 40,000-60,000 U.S. households, between 2004 and 2007. The data contain information about the products households buy, as well as when and where these products were purchased. The Nielsen Homescan data has national coverage and provides wide variation in household location and demographics. Overall, the data include purchases of almost 250 million different items. One of the advantages of this dataset is that it records the bar codes at a very fine level, as well as the expenditure on each of them, allowing us to construct multiple measures of non-durable consumption segregation.

2.3 American Community Survey

The ACS is an annual survey conducted by the Census Bureau that randomly samples individuals in each state, the District of Columbia and Puerto Rico. We use information on income, education, age, race and geography (PUMA and state) from the ACS to validate the representativeness of the Infutor data and to measure residential segregation by race, by income, by age and by education, all of which are important variables in our analysis but are imputed in the Infutor data. We restrict the ACS sample to individuals between 22 and 80 and exclude observations with non-positive income. The income variable we focus on is total household income. Although the car and home characteristics from the Infutor data are at individual level, we view these two consumption categories as likely to be used jointly by all members of a household.

3 Patterns of Consumption Segregation

In this section we describe patterns of consumption segregation across space, time, consumption categories and socio-economic groups. We establish a link between the level of consumption segregation and other characteristics of regions in the United States. We highlight four main findings. First, consumption segregation did not increase in the last 15 years. This is mostly because segregation in non-durable consumption decreased. Second, there is a great degree of regional variation in consumption segregation, especially in durable consumption. Third, consumption is almost 3 times more segregated in richest CBSAs, relative to the poorest. Fourth, consumption segregation is not specific to any particular demographic group.

3.1 Measuring Segregation

Throughout the paper we consider two measures of segregation, depending on whether the variable we consider is categorical or continuous. For categorical variables, such as the car model, we measure segregation using the *entropy index*. For continuous variables, such as income or expenditure we measure segregation using the *rank-order index*. Both measures of segregation are commonly employed in the literature on segregation and capture how representative is the distribution of a certain economic outcome in a geographic sub-unit relative to a broader geographic unit. We next describe these two measures in detail.

Entropy Index. We measure segregation along dimensions that are categorical (e.g. car model, race, categories of groceries) using the entropy index. Our choice has dual motivation. First, it is motivated by the fact that our data on consumption is organized in the form of differentiated consumption categories, thus requiring a multigroup segregation measure. Second, it is motivated by the analysis of Reardon and Firebaugh (2002), who evaluate multiple indices of multigroup segregation and show that the entropy index is the most conceptually and mathematically satisfactory, as it satisfies a large number of desirable properties of segregation indices.[6]

To construct the entropy index for a broad geographic unit, we begin by describing the

[6] We also report robustness results from measuring consumption segregation using a dissimilarity index extended to multigroups. The dissimilarity index is widely used in the segregation literature when comparing two population subgroups (e.g. black and white). We do not use this as out benchmark because Reardon and Firebaugh (2002) show that for multigroup segregation this index does not satisfy many of the desirable properties of segregation indices.

construction of the entropy score, a measure of diversity. The entropy score of a geographic unit i (e.g. i can be street, Census tract, zipcode, city, etc.) is

$$h_i = -\sum_{j=1}^{J} p_{ij} \ln\left(p_{ij}\right), \tag{1}$$

where J is the number of mutually exclusive groups (car or house characteristics in the case of the Infutor data) and p_{ij} is the share of the population of geographic unit i that belongs to group j. Specifically, $p_{ij} = \frac{n_{ij}}{n_i}$, where n_i is the population of the geographic unit i and n_{ij} is the population of the geographic unit i that belongs to group j. For example, if i is a zipcode, then in our case n_i is the total number of cars in geographic unit i and n_{ij} is the total number of cars of of model j in geographic unit i. The maximum value for h_i is $\ln(J)$. A high value of h_i indicates more diversity. The extreme case $h_i = 0$ indicates that the geographic unit i contains only one group.

Based on the measure above, one can calculate segregation for a broader geographic unit (broader than i), such as a state. Specifically, the entropy index of a broader geographic unit is defined as

$$H = \frac{\hat{H} - \bar{H}}{\hat{H}}, \tag{2}$$

where $\hat{H}$ is the entropy index calculated at the level of a broader geographic unit using (1) and $\bar{H}$ is the population share weighted average of h_i, for all geographic units i belonging to the broader unit. The index H is bounded between 0 and 1. A value of $H = 1$ indicates extreme segregation, with each geographic unit i containing only one group (i.e. $\bar{H} = 0$). A value of $H = 0$ indicates no segregation, with each geographic unit i being representative of the broader geographic unit (i.e. $\hat{H} = \bar{H}$).

Rank-order Index. To measure segregation along dimensions that are continuous (e.g. income, consumption expenditure), we employ the rank-order information theory index, a commonly used measure of income segregation (Reardon et al., 2006; Reardon and Bischoff, 2011). The rank-order index of a continuous variable y is given by

$$H^R(y) = 2\int_0^1 \left\{ \sum_{i=1}^{I} \omega_i \left[\bar{F}_{i,p} \ln\left(\frac{\bar{F}_{i,p}}{p}\right) + \left(1 - \bar{F}_{i,p}\right) \ln\left(\frac{1 - \bar{F}_{i,p}}{1-p}\right) \right] \right\} \mathrm{d}p \tag{3}$$

where $\bar{F}_{i,p} = F_i\left(y(p)\right)$ is the cumulative function in the geographic unit i evaluated at $y(p)$, where note that both y and the percentiles p correspond to the income distribution of a geographic unit that is broader than i. The rank-order index H^R is also bounded between 0 and 1, with $H^R = 1$ indicating extreme segregation and $H^R = 0$ indicating no segregation. We note that we obtain similar results if, instead, we measure segregation of continuous variables by using the entropy index applied to bins of the continuous variable, such as income deciles.

Measuring Segregation in the Data. In constructing the moments of segregation reported in the paper, our notion of the geographic unit i is a PUMA (Public Use Microdata Area), the smallest unit of geography that is available across all the datasets that we use. The broader unit of geography is either a CBSA (Core Based Statistical Area) or a US state. In reporting trends, the broader unit of geography is the country.

When measuring segregation at the level of a CBSA we exclude all CBSAs that cover less than two PUMAs, as calculating the entropy index requires that the broader geographic unit contains at least two sub-units of geography i. Specifically, starting with 933 CBSAs, we drop 295 CBSAs that do not include any PUMA (very small CBSAs) and 422 CBSA that map one-to-one into a PUMA. The remaining 216 CBSAs include, on average, 9 PUMAs and cover approximately 80% of the total population.

3.2 Trends in Consumption Segregation

We begin by describing trends in consumption segregation in the United States. We employ several measures of consumption segregation. First, since our data on consumption have both information on the dollar value of the goods consumed as well (e.g. dollars spent on groceries, value of the car, value of the home), as well as on the actual goods consumed (type of groceries purchased, type of car owned), we are able to measure both the segregation of consumption expenditure using the rank-order index, as well as the segregation of consumption itself via the entropy index. Second, our data have an additional layer of detail that allows us to study the segregation of both durable and non-durable consumption, which are known to respond differently to economic shocks and policy (Berger and Vavra, 2014, 2015). Specifically, we measure the segregation of non-durable consumption using the Nielsen Homescan data and the segregation of car and housing consumption using the Infutor data.

We also aggregate entropy indices for the different consumption categories into an aggregate entropy index for total consumption or for total durable consumption using expenditure shares as weights. Specifically, using the CEX we calculate that the spending share on rent and rent equivalent for homeowners is 32%, the spending share on food at home, alcohol at home, tobacco, personal care products and other personal goods is 15% and the spending share on new and used motor vehicles is 4%. These are the three largest components of the household consumption basket (Theloudis, 2020).

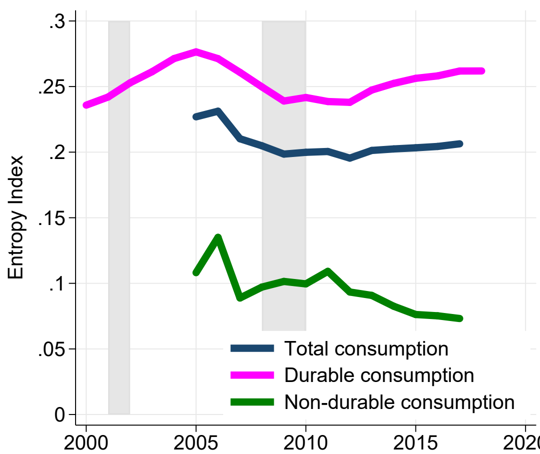
Figure 1 illustrates the trends in consumption segregation in the United States since 2000. Panel (a) of the figure shows the evolution of the segregation of three broad measures of consumption: total consumption, durable consumption and non-durable consumption. We make two remarks. First, durable consumption is more segregated than non-durable consumption. The average of the durable consumption entropy index is 25%, approximately 2.5 times larger than that of non-durable consumption segregation. This indicates that the average PUMA in the United States is 25% less diverse than the country. We return to this point below and show that the large segregation of durable consumption mostly reflects segregation of housing consumption. As a consequence, and in light of the large expenditure share on durables, segregation of total consumption is at an intermediate level, close to the durable consumption segregation. Speficifically, the average total consumption entropy index is 20%. Second, the segregation of non-durable consumption exhibits a downward trend, having declined by approximately 25% since 2005, the beginning of our Nielsen Homescan sample, but durable and total consumption segregation display no trend growth. Fluctuations in durable consumption segregation are cyclical, reflecting the boom-bust cycle in the housing market.

In Panels (b)-(d) of Figure 1 we zoom in on the segregation of consumption categories. Panel (b) depicts the evolution over time of non-durable consumption segregation measured both using data on non-service retail expenditure, as in Panel (a), as well as the specific product categories purchased. The average non-durable consumption expenditure segregation is higher than that measured using product categories that households purchase. That the segregation of non-durable consumption at the level of product categories is non-zero suggests a role for supply-side channels stemming from product availability (Allcott et al., 2019). That the segregation of non-durable spending is higher suggest there are forces beyond product availability that shape segregation of non-durable consumption. We investigate which are these forces below.

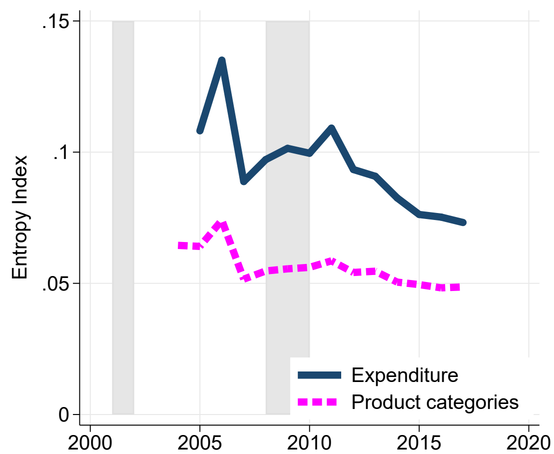
Panels (c) and (d) depict the evolution of housing and car consumption segregation between 2000 and 2018. A first striking feature that emerges is that housing consumption segregation is roughly an order of magnitude higher than car consumption segregation. This is true irrespective of weather we measure the value of homes using directly reported values in the ACS and Census or whether we use the deeds information in the Infutor data. Car consumption segregation is, in fact, the least segregated dimension of consumption, whether we measure it using the values of the cars or car models. A second feature that emerges is that the segregation of housing consumption mirrors the dynamics of house prices more generally, consistent with differential house price appreciation across US regions (Guren et al., 2020). In contrast, the segregation of car consumption displays a steady upward trend.

Figure 1: Consumption Segregation Over Time

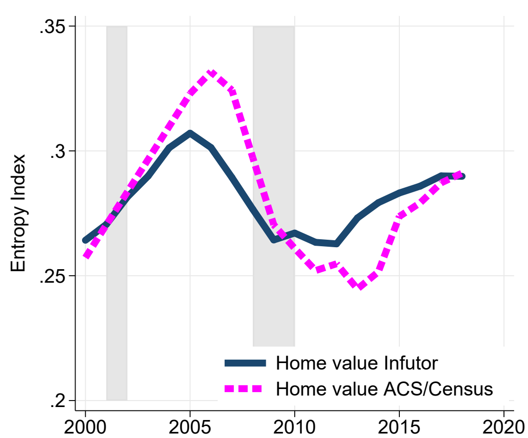
(a) Consumption and Income



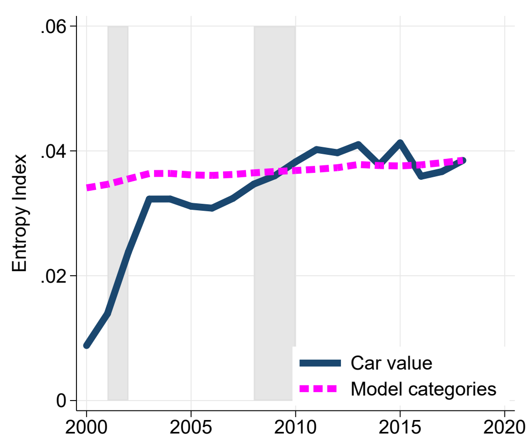
(b) Non-durable consumption



(c) Housing



(d) Cars



3.3 The Geography of Consumption Segregation

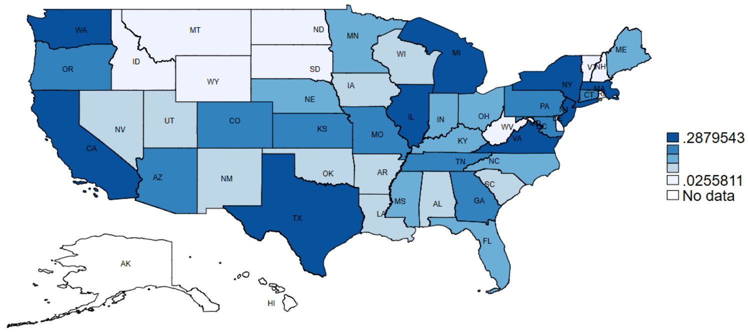
In this section we turn to analyzing the extent of consumption segregation across U.S. regions. Figure 2 offers a visual representation of the geography of consumption segregation. To construct this figure we first compute entropy indices for each consumption category under the assumption that the narrow geographic unit i is a PUMA and the broader geographic unit is a U.S. state.[7] We then report in the figure, for each state, the average of the entropy index over the period 2016-2018.

Panel (a) of Figure 2 reveals substantial heterogeneity in how segregated total consumption is across U.S. states, with the most segregated state is 11 times more segregated than the least segregated state. Specifically, the entropy index varies from 28% in New York to 2.5% in Wyoming. In other words, the average PUMA in New York is nearly 30% less diverse than the state, while in Wyoming the average PUMA is nearly representative of the state. In general, total consumption is most segregated on the West Coast, the North-East and Texas. At the other end, the Rocky Mountain Region exhibits the lowest levels of consumption segregation.

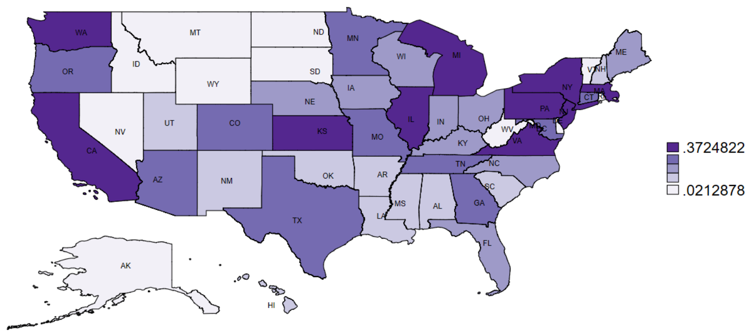
[7] Figure 6 in Appendix B contains a visual representation of the geography of consumption segregation at the level of a CBSA.

Figure 2: State-level Consumption Segregation

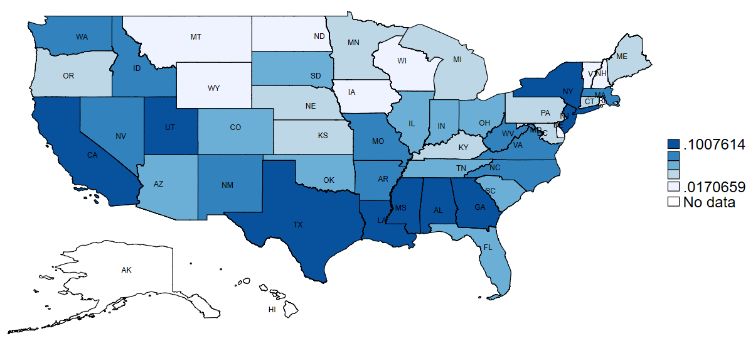
(a) Total consumption



(b) Durable consumption



(c) Non-durable consumption

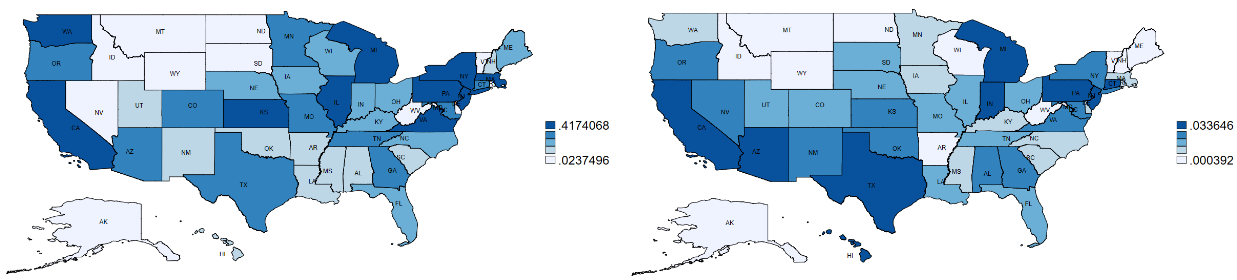


Notes: The figure plots state-level consumption entropy indices averaged over the period 2016-2018.

Panel (b) of Figure 2 depicts the geography of durable and non-durable consumption segregation, respectively. The segregation of durable consumption displays similar patterns as that of total consumption, a reflection of the large share of durable spending in total spending. Specifically, durable consumption is most segregated in New York. At the other end, Wyoming, South Dakota and Alaska are the least segregated. Figure 3 zooms in on the sources of durable consumption segregation. Panel (a) of the figure shows that the segregation of non-durable consumption refects, to a large extent, segregation in housing consumption. The segregation of vehicle consumption, shown in Panel (b) of the figure, exhibits slightly different geography patterns, with higher segregation in the South and less segregation in the North-East, but the level of segregation in this consumption category is, in general, much smaller and close to perfect diversity.

Figure 3: State-level Durable Consumption Segregation

(a) Housing (b) Cars



Notes: The figure plots state-level consumption entropy indices averaged over the period 2016-2018.

Turning to non-durable consumption, Panel (c) of Figure 2 shows that the geography of the segregation of non-durable consumption is different than that of durable consumption. Specifically, while New York and California continue to exhibit among the highest levels of segregation, the figure reveals very high levels of non-durable consumption segregation in the South. The state with the highest level on non-durable consumption segregation is Texas, where the average PUMA is 10% less diverse than the state. At the other extreme, in Vermont the average PUMA is nearly representative of the state.

We next investigate the locus of consumption segregation. To that end, we leverage the additive organizational decomposability of the entropy index, our chosen measure of segregation. Specifically, as shown in Reardon and Firebaugh (2002), assuming that J geographic units are clustered in K clusters ($K < J$), the entropy index H can be rewritten as the sum of $K + 1$ additive components

$$H = H_K + \sum_k \omega_k \frac{h_k}{h} H_k, \tag{4}$$

where ω_k is the population share of the cluster k, h_k is the entropy score of cluster k, h is the national-level entropy score, and H_k is the information theory index of cluster k. The term H_K represents the *between* cluster component, while the remaining K terms represent the portion of total segregation due to segregation *within* cluster. We derive a similar decomposition for the rank-order index H^R. Specifically,

$$H^R = H^R_K + \sum_k \omega_k H^R_k, \tag{5}$$

where, relative to equation (4), the term corresponding to $\frac{h_k}{h}$ is equal to 1 in the case of the rank-order index. The share of total segregation due to the segregation within cluster k represents the amount by which total segregation would fall if segregation within cluster k were eliminated by rearranging individuals among its geographic units while leaving all other geographic units unchanged.

In Table 4 we report the resulting decomposition. The top panel of the table, where we assume that the clusters are U.S. states, shows two-thirds of consumption segregation occurs within states. That is, total consumption segregation were to decrease by approximately 70% if segregation within each state were to be eliminated by appropriately rearranging individuals within the PUMAs of each state. The second and third columns of the table decompose the segregation of durable and non-durable consumption into within and between state components. While it is the case that most of consumption segregation is accounted for by segregation within states even for the two broad consumption categories, we note that in the case of non-durable consumption nearly all segregation is explained by the within state component. Finally, the last two columns of the table provide further detail into the segregation of durable consumption and show that the fact that most of durable consumption segregation is attributable to the within state component is a reflection of housing consumption, which is more segregated within than across states, while segregation of vehicle consumption reflects to a very large extent segregation between states.

The bottom panel of Table 4 performs this decomposition assuming that clusters are CBSAs. Given that CBSAs are geographic units that are smaller than US states and that the within/between state decomposition of segregation reveals a large role for segregation within states, the decomposition of segregation within and between CBSAs offers further detail on the locus of the within state segregation. We find nearly equal contributions of the within and between CBSA components in explaining total consumption segregation, as well as segregation of durable and non-durable consumption.

Table 4: Consumption Segregation Within and Between Regions

	Total consumption	Durable consumption	Non-durable consumption	Housing	Cars
			State-level segregation		
Between states	0.285	0.392	0.036	0.350	0.727
Within state	0.715	0.608	0.964	0.650	0.273
			CBSA-level segregation		
Between CBSAs	0.444	0.569	0.557	0.670	0.166
Within CBSA	0.556	0.431	0.443	0.330	0.834

Notes: The table reports averages of the between and within region components over the period 2016-2018.

Motivated by the observed heterogeneity in consumption segregation across the United States, in Table 5 we investigate how the level of consumption segregation varies with socio-economic characteristics of CBSAs.[8] We compute the average entropy index for total, durable and non-durable consumption for CBSAs that belong to the top 25% or the bottom 25% of the national distribution of various socio-economic characteristics: income, education, race, age and population size. The table shows that consumption segregation is larger in CBSAs that are richer, younger, larger, and where a large share of the population has a college degree and a small share of the population is white. For example, total consumption is 2.5 times more segregated in CBSAs that are in the top 25% of the distribution of income in the United States than in those in the bottom 25% of the distribution. The relative segregation between rich and poor CBSAs extends across broad consumption categories, with durable consumption being 2.7 times more segregated and non-durable consumption 1.9 times more segregated in rich CBSAs. The same decomposition by education provides similar results, being education and income highly correlated. When we decompose by race, total consumption is 2 times more segregate in CBSAa that are in the bottom 25% of the distribution of share of whites. The results are stronger for durable consumption than for non-durable. Differences by age, instead, are much more muted. Finally, when decomposing the measures by population, we find that the consumption segregation is 4.3 times higher in CBSAs that are in the top 25% of the distribution of population. Overall, these results suggest a strong heterogeneity of consumption segregation by core demographic characteristics.

[8]Table 16 reports how consumption segregation varies with characteristics of US states.

Table 5: Consumption Segregation and Regional Characteristics

	Total consumption	Durable consumption	Non-durable consumption
		By income	
Bottom 25%	0.058	0.063	0.040
Top 25%	0.144	0.169	0.075
		By education (college share)	
Bottom 25%	0.063	0.068	0.044
Top 25%	0.134	0.154	0.075
		By race (share white)	
Bottom 25%	0.136	0.152	0.087
Top 25%	0.060	0.069	0.036
		By age (share $\leq$ 35)	
Bottom 25%	0.076	0.088	0.046
Top 25%	0.103	0.110	0.072
		By population	
Bottom 25%	0.028	0.032	0.018
Top 25%	0.121	0.136	0.076

Notes: The table reports population weighted averages of CBSA-level consumption entropy indices over the period 2016-2018.

We next turn to a more in depth characterization of how consumption segregation varies with demographic characteristics of individuals rather than of space. In Table 6 we report consumption segregation for demographic groups. The top panel of the table stratifies individuals in our sample in three race groups and computes the entropy index H^R defined in equation (3) for each racial group. We find little variation in the segregation of total consumption at the level of a racial group, reflecting to a large extent little variation in the segregation of durable consumption. We find more pronounced differences between racial groups for non-durable consumption. Specifically, whites have the highest segregation of non-durable consumption, similar to that of Blacks, but 37% higher than that of other racial groups. The middle panel of the table reports average consumption segregation for college educated and non-college educated individuals. Total consumption is 13% more segregated among the college educated, reflecting an 11% higher durable consumption segregation and a 19% higher non-durable consumption segregation among individuals belonging to this group. Finally, the bottom panel of the table shows nearly no difference in consumption segregation by age. That is, there is no difference between how diverse is the consumption of the old in the average PUMA relative to the CBSA, and how diverse is that of the young.

Table 6: Consumption Segregation by Demographic Group

	Total consumption	Durable consumption	Non-durable consumption
		By race	
White	0.102	0.111	0.071
Black	0.108	0.116	0.068
Other	0.115	0.124	0.052
		By education	
No college degree	0.102	0.107	0.079
College degree	0.115	0.119	0.094
		By age	
Younger than 35	0.104	0.118	0.058
Older than 35	0.104	0.117	0.064

Notes: The table reports population weighted averages of CBSA-level consumption entropy indices over the period 2016-2018.

The result above suggests a small role for differences across demographic groups in terms of consumption segregation. We investigate this more systematically by decomposing consumption segregation into *within* and *between* demographic groups components. We consider both the broad demographic groups defined in Table 6, as well as narrow demographic groups defined as $(race, education, age)$ tuples.[9] We perform a decomposition that is analogous to that described in equation (5), relying on the additive group decomposability property of the entropy and rank-rank order indices (Reardon and Firebaugh, 2002).[10]

Table 7 summarizes the results of this decomposition and shows that most of the segregation in consumption is accounted for by the within demographic group component, and

[9]Specifically, we consider all combinations of three racial groups (white, Black, other), two education groups (with college degree, without college degree) and two age groups (younger than 35, older than 35).

[10]For the purpose of this decomposition, the geographic unit i in equation (1) is a combination between a PUMA and a demographic group.

there is only a very small role for differences in segregation across demographic groups for understanding the overall patterns of consumption segregation. Overall these results suggest that differences among demographic groups do not account for a large share of consumption segregation, instead geographic differences, especially by income and education of regions have a much higher explanatory power.

Table 7: Consumption Segregation Within and Between Demographic Groups

	Total consumption	Durable consumption	Non-durable consumption
		Race	
Between group	0.033	0.009	0.091
Within group	0.967	0.991	0.909
		Education	
Between group	0.028	0.034	0.012
Within group	0.972	0.966	0.988
		Age	
Between group	0.014	0.007	0.029
Within group	0.986	0.993	0.971
		Race $\times$ *Education* $\times$ *Age*	
Between group	0.033	0.042	0.007
Within group	0.967	0.958	0.993

Notes: The table reports averages of the between and within demographic group components over the period 2016-2018.

4 What Drives Consumption Segregation?

What explains consumption segregation? There is a long line of work studying segregation in the United States over the past century along various socio-economic dimensions (race, education, income, ethnicity).[11] We analyze next to what extent residential segregation along these previously documented margins is a driver of consumption segregation, thus providing a bridge between previously studied dimensions of residential segregation and the residential

[11] See Trounstine (2018) for a comprehensive summary of this work.

segregation of welfare. To answer this question we estimate the regression specification

$$\ln H_{C,rt} = \alpha_0 + \alpha_1 \ln H_{Y,rt} + \alpha_2 \ln H_{R,rt} + \alpha_3 \ln H_{E,rt} + \alpha_4 \ln H_{A,rt} + \boldsymbol{\gamma} \mathbf{X}_{rt} + \delta_t + \varepsilon_{rt}, \quad (6)$$

where $H_{C,rt}$, $H_{Y,rt}$, $H_{R,rt}$, $H_{E,rt}$, and $H_{A,rt}$ denote the entropy indices of consumption, income, race, education, and age in CBSA r and year t, respectively, $\mathbf{X}_{rt}$ is a vector of time varying controls for CBSA r, and δ_t are year fixed effects. The measures of consumption and income segregation are calculated as described in equation (3), while the measures of racial, education, and age segregation are calculated as described in equation (2), considering the same racial, education and age groups as in Section 3.3. Motivated by the analysis in Section 3.3, the vector of controls includes average income in CBSA r in year t, as well as the population share of whites, Blacks, college educated and younger than 35.

Table 8 reports the results of the estimation, sequentially augmenting the set of controls for segregation.[12] Specifically, the specification in column (1) only controls for segregation by income, in addition to the set of controls $\mathbf{X}_{rt}$ and the time fixed effects. Column (2) adds a control for racial segregation and column (3) adds controls for segregation by education and age. Focusing on the specification in column (1) for total consumption we find an elasticity of total consumption segregation to income segregation of 0.67. That is, 67% of income segregation translates into consumption segregation. The R^2 we obtain from estimating equation (6) without any residential segregation controls is 0.41. Comparing this with the R^2 reported in column (1) suggests that differences in income segregation across CBSAs explain 30% of the differences in consumption segregation. In column (2), we include in the specification a control for racial segregation and find that while the estimated elasticity of consumption segregation with respect to racial segregation is also positive, 0.14, it is four times smaller than that with respect to income segregation. Additionally, the R^2 only increases by two percentage points. In column (3), we add to the specification controls for segregation by education and by age. We continue to find that income segregation is the main driver of consumption segregation. We also find a sizable role for segregation by education, but note that segregation by income and by education are strongly correlated. Specifically, the correlation coefficient between the two is 0.77. We interpret the two as broadly representing economic status. Segregation by education and by age explain an additional 4% of the difference in consumption segregation across CBSAs, further strengthening the role of differences in income segregation as the main driver of differences in consumption segregation.

[12]See Table 18 in Appendix B for the corresponding results exploiting variation across U.S. states.

That income segregation emerges as a main driver of consumption segregation is in line with the findings of the existing literature on residential segregation and the standard consumption theory. Specifically, Massey et al. (2009) document that during the last third of the twentieth century, the United States moved from a regime of segregation based on race and ethnicity to a regime of segregation based on economic status, where economic status is given by income and education. Standard consumption theory predicts that differences in income across individuals are expected to translate in differences in consumption if income differences are persistent and/or if credit market frictions or other form of market incompleteness prevent individuals to insure against income fluctuations. Extended to a spatial dimension, as in Giannone et al. (2019), this argument suggests that, under the same conditions, residential segregation by income will translate into residential segregation by consumption.

Table 8: Drivers of Consumption Segregation

	Total consumption			Durable consumption			Non-durable consumption		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$\ln H_Y$	0.67***	0.58***	0.39***	0.87***	0.73***	0.43***	0.44***	0.35***	0.24***
	(0.03)	(0.04)	(0.06)	(0.05)	(0.05)	(0.07)	(0.03)	(0.04)	(0.05)
$\ln H_R$		0.14***	0.10**		0.21***	0.16***		0.14***	0.12***
		(0.05)	(0.05)		(0.07)	(0.06)		(0.04)	(0.03)
$\ln H_E$			0.21***			0.33***			0.11***
			(0.05)			(0.06)			(0.03)
$\ln H_A$			0.02			0.01			0.04
			(0.02)			(0.03)			(0.03)
R^2	0.72	0.74	0.78	0.65	0.66	0.73	0.57	0.59	0.61

Notes: The table reports the estimates of α_1, α_2, α_3 and α_4 in equation (6). The estimate of α_0, the time fixed effects and the estimate of the vector $\boldsymbol{\gamma}$ are omitted. Robust standard errors are reported in parentheses. The regression is estimated with population weights based on the 2010 Census. ***, **, and *, represent statistical significance at 1%, 5% and 10%, respectively.

Turning to the drivers of durable and non-durable consumption segregation, we draw a similar conclusion. Specifically, we find that in the most conservative specification 43% of income segregation translates into durable consumption segregation. This elasticity is approximately half for non-durable consumption: only 24% of income segregation translates into non-durable consumption segregation. Relative to the R^2 from a regression that abstracts from any controls from segregation, we find that differences in income segregation across CBSAs account for 33% of the differences in durable consumption segregation, while segregation by race, by education and by age account for an additional 8%. Differences in non-durable consumption segregation across CBSAs are accounted for in proportion of 22% by differences in income segregation and by an additional 4% by differences in segregation by race, by education and by age.[13]

We next analyze whether how the relationship between income and consumption segregation varies with socio-economic characteristics of CBSAs. To that end we project consumption segregation on income segregation and income segregation interacted with a dummy variable that is equal to one if the CBSA is in the op 25% of the national distribution of a given socio-economic characteristic. We consider the same characteristics of regions as in Table 5: average income, the share of the population with a college degree, the share of the population that is white, the share of the population that is younger than 35 and the population size. In each regression we include a separate dummy variable for the socio-economic characteristic under consideration and the same control variables as in equation (6), but exclude the control for the socio-economic characteristic under consideration. For example, when we analyze whether the relationship between income and consumption segregation is different for CBSAs that are in the top 25% of the income distribution we include a dummy that is equal to one if this is the case, but exclude the control for average income. The table shows that extent to which income segregation translates into consumption segregation does not depend on whether the region is rich or has a large share of the population being college educated, white or young. However, income segregation does appear to translate more strongly into consumption segregation in larger CBSAs, and the effect is both economically and statistically significant.

Heterogeneity. Before we inspect the mechanisms through which income segregation does translate into consumption segregation, we study how heterogeneous this relationship is based on local characteristics of CBSAs. Table 9 reports the results for such tests. We find that when interacting income segregation with a dummy equal to 1 if a CBSA is in the top 25% of income, education, share of white, young and population, the only strong and significant source of heterogeneity is population. This suggest that the correlation between income and consumption segregation is much higher in large CBSAs. This aligns with the fact that overall segregation is much larger in more populated areas and suggests that in

[13]The R^2 from regressing durable consumption segregation on the controls in equation (6), excluding the segregation controls, is 0.32. The corresponding R^2 for non-durable consumption segregation is 0.35.

these locations there could be mechanisms in place that prevent income segregation from washing out in terms of consumption.

Table 9: Drivers of Consumption Segregation, Heterogeneity

	Total consumption	Durable consumption	Non-durable consumption
		By income	
$\ln H_Y$	0.60***	0.83***	0.34***
	(0.05)	(0.08)	(0.05)
$\ln H_Y \times \mathbf{1}_{\text{Top 25\%}}$	0.23	0.09	0.15*
	(0.16)	(0.18)	(0.08)
		By education (college share)	
$\ln H_Y$	0.61***	0.82***	0.41***
	(0.05)	(0.08)	(0.05)
$\ln H_Y \times \mathbf{1}_{\text{Top 25\%}}$	0.10	0.11	0.008
	(0.08)	(0.13)	(0.07)
		By race (share white)	
$\ln H_Y$	0.69***	0.87***	0.48***
	(0.06)	(0.05)	(0.07)
$\ln H_Y \times \mathbf{1}_{\text{Top 25\%}}$	-0.06	-0.12	-0.11
	(0.09)	(0.09)	(0.08)
		By age (share $\leq$ 35)	
$\ln H_Y$	0.67***	0.77***	0.52***
	(0.05)	(0.06)	(0.04)
$\ln H_Y \times \mathbf{1}_{\text{Top 25\%}}$	-0.03	0.06	-0.02
	(0.10)	(0.12)	(0.07)
		By population	
$\ln H_Y$	0.14	0.23**	-0.02
	(0.09)	(0.09)	(0.07)
$\ln H_Y \times \mathbf{1}_{\text{Top 25\%}}$	0.60***	0.71***	0.26**
	(0.15)	(0.16)	(0.11)

Notes: The table reports slope coefficients from regressing consumption segregation on income segregation and income segregation interacted with a dummy variable that equals 1 if a CBSA is in the top 25% of the national distribution of income, share of the population that is college eduated, white, younger than 35, and population, respectively. All regressions include separate controls for the dummy variable previously described and, as well as the set of controls in equation (6). All other coefficients are omitted in the interest of space. With the exception of the last panel, all regressions are estimated with population weights based on the 2010 Census. ***, **, and *, represent statistical significance at 1%, 5% and 10%, respectively.

On the whole, these results suggest an important role for income segregation as a driver of consumption segregation, and a more muted but still significant role for racial segregation. Income segregation appears to be a stronger driver of consumption segregation in regions that are larger, but the strength of the relationship does not depend on other socio-economic characteristics of regions.

5 Inspecting the Relationship Between Income and Consumption Segregation

Motivated by the results above, in this section we inspect what is the mechanism driving the strong positive relationship between income and consumption segregation. To that end, we scrutinize three potential explanations: market incompleteness, persistent income differences and conspicuous consumption. Market incompleteness, or the lack of access to some financial products (either because of these products being absent or because of underlying informational frictions) and persistent income shocks have the potential to generate such a positive relationship since they prevent consumption insurance among individuals with different income. Instead, conspicuous consumption can reduce the segregation of visible consumption goods, even in the presence of income segregation. We next inspect the data for evidence or lack thereof of each of these hypotheses separately.

5.1 Market Incompleteness vs Persistent Income Shocks

We begin by outlining a simple framework to guide our empirical investigation and then test the predictions of this theory.

5.1.1 An Analytical Framework

We consider the utility maximization problem of a household i who lives in region r in year t. Each period the household earns stochastic income y^i_{rt} and chooses the optimal path of consumption c^i_{rt} and savings a^i_{rt+1} that maximizes its expected life-time utility

$$\mathbf{E}_0 \sum_{t=0}^{\infty} \beta^t u\left(c^i_{rt}\right),$$

subject to the budget constraint

$$c^i_{rt} + \frac{a^i_{rt+1}}{r} = y^i_{rt} + a^i_{rt}$$

and a borrowing constraint $a^i_{rt+1} \geq \underline{a}$. Here, β is the discount factor of the household, r is the real interest rate on savings and $\underline{a}$ is the borrowing limit. The optimal consumption-saving choice is characterized by the Euler equation

$$u'(c^i_{rt}) = \beta(1+r)\mathbf{E}_t u'(c^i_{rt+1}) + \mu_t,$$

where μ_t is the multiplier on the borrowing constraint. That is, when deciding how much to save, the household compares the cost of saving an additional unit of income, expressed in terms of the marginal utility of lost consumption, with the discounted benefit of having an additional unit of resources available for consumption in the following period.

In order to derive an analytical characterization of optimal consumption choices, we specialize this model to what is commonly called the strict permanent income hypothesis. Specifically, we assume that *(i)* households have quadratic utility $u(c) = b_1 c + \frac{1}{2} b_2 c^2$, where the parameters b_1 and b_2 are such that the utility function is strictly increasing and strictly concave, *(ii)* the interest on savings equals the inverse of the discount rate $\beta(1+r) = 1$, and *(iii)* there is no borrowing constraint. Under these assumptions, it can be easily shown that consumption is a martingale

$$c^i_{rt} = \mathbf{E}_t c^i_{rt+1} \quad \text{and, more generally,} \quad c^i_{rt} = \mathbb{E}_t c^i_{rt+j}, \forall j \geq 0.$$

Iterating forward on the budget constraint, taking the limit as $t \to \infty$ and using a No-Ponzi scheme condition gives

$$c^i_{rt} = \frac{r}{1+r}\left[a^i_{rt} + \sum_{j=0}^{\infty}\left(\frac{1}{1+r}\right)^j \mathbb{E}_t y^i_{rt+j}\right],$$

that is, consumption is the annuity value of human and financial wealth. It can then be shown that the change in consumption $\Delta c^i_{rt} \equiv c^i_{rt} - c^i_{rt-1}$ is equal to

$$\Delta c^i_{rt} = \frac{r}{1+r}\sum_{j=0}^{\infty}\left(\frac{1}{1+r}\right)^j \left(\mathbb{E}_t - \mathbb{E}_{t-1}\right) y^i_{rt+j}$$

and is proportional to the the revision in expected earnings due to the new information accruing between $t-1$ and t.

To make further analytical progress, we specialize the process for income by assuming that

$$y^i_{rt} = \rho y^i_{rt-1} + \varepsilon^i_{rt},$$

where ε is a mean-zero shock with variance σ_ε^2 that is iid across households, regions and over time, and ρ is the persistence parameter. Under this specialized income process, consumption dynamics are given by

$$\Delta c_{rt}^i = \frac{r}{1+r-\rho}\varepsilon_{rt}^i.$$

This expression nests two special cases. First, when $\rho = 0$ shocks to income are transitory and consumption evolves according to $\Delta c_{rt}^i = \frac{r}{1+r}\varepsilon_{rt}^i$, implying that the households consume only the annuity value of the shock and that most of it is saved. However, if there are no asset markets, then, $c_{rt}^i = y_{rt}^i$ and, consequently, $\Delta c_{rt}^i = \varepsilon_{rt}^i$, so income shocks translate entirely into consumption. Second, when $\rho = 1$ shocks to income are permanent, and consumption evolves according to $\Delta c_{rt}^i = \varepsilon_{rt}^i$, implying that the shocks translates entirely into consumption.

Zooming out and focusing on the distributions of income and consumption in a given region, the discussion above makes it clear that if income shocks are permanent, then the two distributions mirror each other. If we think about the regions r as being part of a broader geographic unit, such as a state or a CBSA, then the segregation of income within the broader geographic unit should be reflected entirely in the segregation of consumption. In general, how closely the distribution of consumption tracks that of income depends on how persistent income shocks are: the more persistent they are, the closer are the two distributions.

If, instead, income shocks are transitory, the distribution of consumption is less reflective of the distribution of income (i.e. the term $\frac{r}{1+r} \approx 0.02$ for values of r typically used in the literature), as agents can use saving and borrowing to smooth consumption in response to this type of shocks. Once more, thinking of regions r as being part of a broader geographic unit, this implies that income segregation translates into consumption segregation only to a limited extent. However, if asset markets that allow for saving and borrowing are absent (this is what we refer to as market incompleteness), then the two distributions become more intimately linked, as in the case of permanent/persistent income shocks.

5.1.2 Empirics

In this section, we set up a test that allows us to assess whether the strong correlation we observe in the data between income and consumption segregation reflects permanent income differences between socio-economic groups or is, instead, a reflection of incomplete asset markets that prevent consumption insurance against potentially insurable income shocks.

To that end, we decompose the mapping between income and consumption segregation in two components meant to capture how income segregation translates into within- and between-group consumption segregation. The rationale behind this decomposition follows Krueger and Perri (2006) and is based on the assumption that income differences between socio-economic groups can be attributed to fixed characteristics of households. Since it is likely very hard to insure against these differences, an increase in income segregation should translate into an increase in between-group consumption segregation. Within a socio-economic group, the assumption is that income differences arise as a consequence of idiosyncratic income shocks. If there exist financial markets that can facilitate partial insurance against these shocks, then income segregation should translate into within-group consumption segregation only to a limited extent.[14]

To formally investigate this, recall that in Section 3.3 we decomposed consumption segregation into a within demographic group and a between demographic group component, where a demographic group is defined as a $(race, education, age)$ tuple. Letting $H_{C,rt}$ denote the level of consumption segregation in region r in year t, the decomposition allows us to write

$$H_{C,rt} = H^B_{C,rt} + H^W_{C,rt},$$

where $H^B_{C,rt}$ denotes the between-group component of consumption segregation and $H^W_{C,rt}$ denotes the within group component. We then investigate the relative extent to which income segregation affects these two components of income segregation by estimating the following regression specification

$$H^i_{C,rt} = \alpha^i_0 + \alpha^i_1 \; H_{Y,rt} + \boldsymbol{\gamma^i} \mathbf{X}_{rt} + \delta^i_t + \varepsilon^i_{rt},$$

where $i \in \{B, W\}$ and $\mathbf{X}_{rt}$ is the same vector of controls as in (6). Similarly, by estimating

$$H_{C,rt} = \alpha_0 + \alpha_1 \; H_{Y,rt} + \boldsymbol{\gamma} \mathbf{X}_{rt} + \delta_t + \varepsilon_{rt},$$

it can be shown that $\alpha_1 = \alpha^B_1 + \alpha^W_1$. Therefore, the share $\frac{\alpha^B_1}{\alpha_1}$ is informative of the relative importance of permanent income differences in explaining consumption segregation, while $\frac{\alpha^W_1}{\alpha_1}$ is indicative of the importance of market incompleteness.

Table 10 reports the estimates of α_1, α^B_1 and α^W_1 for total consumption, as well as for consumption sub-categories. We find that the between-group component accounts for 14% of the relationship between income and total consumption segregation relationship at CBSA-level, while the within-group component accounts for the bulk of this relationship, 86%. That

[14] An extreme example is that of hand-to-mouth consumers, who cannot insure at all against transitory income shocks. For such consumers, income segregation translates one-to-one in consumption segregation. At the other extreme, when markets are complete, income segregation does not translate at all in consumption segregation.

the within component is the primary driver of the relationship is true also at the level of broad consumption categories (i.e. durable and non-durable consumption), as well as at the level of specific durable consumption categories. The within-group component is relatively more important in explaining the relationship between income segregation and the segregation of durable consumption, especially so in the case of housing, consistent with frictions in the housing market that limit households' ability to smooth consumption fluctuations (Boar et al., 2020). Specifically, 90% of the mapping between income segregation and housing consumption segregation is accounted for by the within group component, while in the case of non-durable consumption this component accounts for 80% of the relationship.[15]

Overall, we conclude that while there is a role for permanent income differences in explaining why consumption is not equalized across space, market incompleteness plays the major role in explaining why income segregation translates into consumption segregation.

Table 10: Consumption and Income Segregation

	Total	Between	Within
Total consumption	1.52	0.21	1.32
α_1^i/α_1		13.8%	86.2%
Non-durable consumption	0.64	0.13	0.51
α_1^i/α_1		20.3%	79.7%
Durable Consumption	1.94	0.16	1.76
α_1^i/α_1		9.7%	90.3%
Cars	0.17	0.03	0.14
α_1^i/α_1		17.6%	83.4%
Housing	2.16	0.21	1.94
α_1^i/α_1		9.7%	90.3%

Notes: The table reports the estimates of α_1, α_1^B and α_1^W. All estimates are significant at 1% significance. Robust standard errors, time fixed effects and the estimates of $\boldsymbol{\gamma^i}$ and $\boldsymbol{\gamma}$ are omitted but are included in the estimation. The regression is estimated with population weights based on the 2010 Census, using data for the 2016-2018 period.

[15] These patterns continue to hold at state-level, as shown in Table 19 in Appendix B.

5.2 Conspicuous Consumption

We now turn to investigating whether conspicuous consumption motives affect the relationship between income and consumption segregation. Conspicuous consumption is a term coined by Veblen (1899) to characterize the idea that "consumption is evidence of wealth, and thus becomes honorific, and [...] failure to consume a mark of demerit".

5.2.1 A Framework

We follow closely Charles et al. (2009) and Glazer and Konrad (1996) in postulating the static utility maximization problem of a household i who lives in region r and earns stochastic income y_r^i drawn from a distribution with finite support. The household divides income into spending on visible consumption goods c_r^i and on goods that are not observable to the society $y_r^i - c_r^i$. The household derives separable utility from consuming the visible and non-visible goods, as well as from the income status

$$u\left(c_r^i\right) + v\left(y_r^i - c_r^i\right) + w\left(s_r^i\right),$$

where u, v and w are strictly increasing and concave utility functions, and s_r^i represents the status of the household or, in other words, the belief that the society has about the income of the household based on the observed consumption of the visible good $s_r^i = \mathbb{E}\left(y_r^i | c_r^i\right)$. In equilibrium, the household chooses the optimal division of income between the visible and non-visible good to maximize utility subject to the constraint that the society's belief about its income is correct and $s_r^i\left(c_r^i\left(y_r^i\right)\right) = y_r^i$.

The prediction of this framework that is of highest relevance for the analysis in this paper is that spending on the visible good c_r^i is increasing in income y_r^i.[16] This, in turn, has implications for the relationship between income and consumption segregation. Let r_l and r_h be regions in a broader geographic unit, such as a state or a CBSA. Consider the case of extreme income segregation in the broader geographic unit, so that all low-income households live in region r_l and all high-income households live in region r_h. If households exhibit a conspicuous consumption motive in that they derive utility from status, then low-income households consume the visible good in order to signal status and differences in spending on the visible good between the two regions are smaller than differences in income, rendering visible consumption segregation smaller than income segregation.

[16] We refer the reader to Charles et al. (2009) and Glazer and Konrad (1996) for a more in depth discussion of this result, as well as other predictions of the framework. We omit these here as the framework is virtually identical to theirs.

5.2.2 Empirics

We next set up a test that allows us to gauge whether a conspicuous consumption motive may be at play in the data. To that end, we leverage the fact that cars are are more visible than the other consumption categories that we consider, especially non-durable consumption. If the conspicuous consumption hypothesis is borne by the data, then we should see that the relationship between income and consumption segregation be weaker for car consumption than for non-durable consumption. In relative terms, this means that the relationship between income segregation and the ratio between cars segregation and total consumption segregation (or non-durable consumption) should be negative. To test this hypothesis, we estimate the following specification

$$\ln \frac{H_{Car,rt}}{H_{C,rt}} = \alpha_0 + \alpha_1 \ln H_{Y,rt} + \boldsymbol{\gamma}\mathbf{X}_{rt} + \delta_t + \varepsilon_{rt},$$

where $\mathbf{X}_{rt}$ is the same vector of controls as in (6). We alternate our dependent variable with $\ln \frac{H_{Car,rt}}{H_{ND,rt}}$ as a robustness test, where $H_{ND,rt}$ denotes the entropy index of non-durable consumption in region r in year t.

Table 11 reports the results of the estimation for our primary unit of geography, CBSA. In the first two columns the dependent variable is (the logarithm of) the ratio between car segregation and total consumption segregation, while in the last two columns the the dependent variable is (the logarithm of) the ratio between car segregation and non-durable consumption segregation. We find that all estimates of α_1 are negative, implying that CBSAs where income segregation is higher the segregation of car consumption is lower relative to the segregation of total or non-durable consumption. This suggests the presence of a conspicuous consumption motive, consistent with Charles et al. (2009), that dampens the extent to which income segregation translates into consumption segregation.

Our finding also suggests that income segregation might generate an externality through consumption by shaping consumption baskets towards more visible goods. In turn, this might affect wealth inequality at an aggregate level. Therefore, understanding the magnitude and the impact of such an externality can contribute to our understanding of the drivers of wealth inequality.

6 Conclusion

We use a novel data source combined with existing data to characterize consumption segregation in the United States and to understand what are the its drivers. We characterize how

Table 11: Test for Conspicuous Consumption

	$\ln \frac{H_{Car}}{H_C}$	$\ln \frac{H_{Car}}{H_C}$	$\ln \frac{H_{Car}}{H_{ND}}$	$\ln \frac{H_{Car}}{H_{ND}}$
$\ln H_Y$	-2.37***	-1.45***	-2.66***	-0.03
	(0.02)	(0.03)	(0.09)	(0.92)
Time FE	Yes	Yes	Yes	Yes
$\mathbf{X}_{rt}$ controls		Yes		Yes

Notes: Estimates of $\boldsymbol{\gamma}^{\boldsymbol{i}}$ and $\boldsymbol{\gamma}$ are omitted but are included in the estimation. The regression is estimated with population weights based on the 2010 Census, using data for the 2016-2018 period. ***, **, and *, represent statistical significance at 1%, 5% and 10%, respectively.

consumption segregation varies over time, regions, consumption categories and demographic groups. We find large spatial heterogeneity in consumption segregation patterns. Specifically, New York, the most segregated state, is 11 times more segregated than Wyoming, the least segregated one. Consumption segregation is substantially larger in regions that are richer, more educated, larger and have a lower share of the population that is white.

We investigate what drives consumption segregation and find that when accounting for different types of segregation that have been previously documented, such as segregation by income, race, education and age, income segregation emerges as the main driver. We also find a role, albeit more muted, for racial segregation. Motivated by this finding, we disentangle potential mechanisms that may generate the observed relationship between income and consumption segregation. We are able to separate the role of market incompleteness and permanent income differences and find that the former accounts for a significantly larger share of the observed relationship. We also find suggestive evidence of conspicuous consumption, a motive that goes in the direction of dampening the relationship between income and consumption segregation.

We believe this paper presents evidence on a topic often discussed by academic and policy makers, for which little was empirically known. Thanks to growing data availability, we present new evidence. One of our contributions will be also to release measures of consumption segregation at different levels of geography, over time and for demographic groups, in the hope that they can be used for both empirical work on geographical differences and sorting as well as for the estimation of structural models of consumption and space.

References

Agarwal, Sumit, J. Bradford Jensen, and Ferdinando Monte, "Consumer Mobility and the Local Structure of Consumption Industries," Working Paper 23616, National Bureau of Economic Research July 2017.

Aguiar, Mark A, Mark Bils, and Corina Boar, "Who Are the Hand-to-Mouth?," Technical Report, National Bureau of Economic Research 2020.

Aguiar, Mark and Erik Hurst, "Measuring trends in leisure: The allocation of time over five decades," *The Quarterly Journal of Economics*, 2007, *122* (3), 969–1006.

— **and Mark Bils**, "Has Consumption Inequality Mirrored Income Inequality?," *American Economic Review*, September 2015, *105* (9), 2725–56.

Allcott, Hunt, Rebecca Diamond, Jean-Pierre Dubé, Jessie Handbury, Ilya Rahkovsky, and Molly Schnell, "Food Deserts and the Causes of Nutritional Inequality," *The Quarterly Journal of Economics*, 05 2019, *134* (4), 1793–1844.

Andreski, Patricia, Geng Li, Mehmet Zahid Samancioglu, and Robert Schoeni, "Estimates of annual consumption expenditures and its major components in the PSID in comparison to the CE," *American Economic Review*, 2014, *104* (5), 132–35.

Berger, David and Joseph Vavra, "Measuring How Fiscal Shocks Affect Durable Spending in Recessions and Expansions," *The American Economic Review*, 2014, *104* (5), 112–115.

— **and** — , "Consumption Dynamics During Recessions," *Econometrica*, 2015, *83* (1), 101–154.

Bernstein, Shai, Rebecca Diamond, Timothy J. McQuade, and Beatriz Pousada, "The Contribution of High-Skilled Immigrants to Innovation in the United States," Working Paper 2018.

Blundell, Richard, Luigi Pistaferri, and Ian Preston, "Consumption Inequality and Partial Insurance," *American Economic Review*, December 2008, *98* (5).

Boar, Corina, "Dynastic precautionary savings," Technical Report, National Bureau of Economic Research 2020.

— , **Denis Gorea, and Virgiliu Midrigan**, "Liquidity Constraints in the U.S. Housing Market," Working Paper 23345, National Bureau of Economic Research April 2020.

Brouillette, Jean-Felix, Charles I. Jones, and Peter J. Klenow, "Race and Economic Well-Being in the United States," Working Paper 2020.

Chao, Angela and Juliet B. Schor, "Empirical tests of status consumption: Evidence from women's cosmetics," *Journal of Economic Psychology*, 1998, *19* (1), 107–131.

Charles, Kerwin Kofi, Erik Hurst, and Nikolai Roussanov, "Conspicuous consumption and race," *The Quarterly Journal of Economics*, 2009, *124* (2), 425–467.

Couture, Victor, Cecile Gaubert, Jessie Handbury, and Erik Hurst, "Income Growth and the Distributional Effects of Urban Spatial Sorting," Working Paper 26142, National Bureau of Economic Research August 2019.

Cutler, David M and Lawrence F Katz, "Rising Inequality? Changes in the Distribution of Income and Consumption in the 1980's," *American Economic Review*, May 1992, *82* (2), 546–551.

Davis, Donald R, Jonathan I Dingel, Joan Monras, and Eduardo Morales, "How Segregated is Urban Consumption?," Technical Report, National Bureau of Economic Research 2017.

Diamond, Rebecca and Enrico Moretti, "The Geography of Consumption Inequality," Technical Report 2020.

— , **Tim McQuade, and Franklin Qian**, "The effects of rent control expansion on tenants, landlords, and inequality: Evidence from San Francisco," *American Economic Review*, 2019, *109* (9), 3365–94.

Dolfen, Paul, Liran Einav, Peter J Klenow, Benjamin Klopack, Jonathan D Levin, Laurence Levin, and Wayne Best, "Assessing the Gains from E-Commerce," Working Paper 25610, National Bureau of Economic Research February 2019.

Fisher, Jonathan D., David S. Johnson, and Timothy M. Smeeding, "Measuring the Trends in Inequality of Individuals and Families: Income and Consumption," *American Economic Review*, May 2013, *103* (3), 184–88.

Fogli, Alessandra and Veronica Guerrieri, "The End of the American Dream? Inequality and Segregation in US Cities," Working Paper 26143, National Bureau of Economic Research August 2019.

Ganong, Peter and Pascal Noel, "Consumer spending during unemployment: Positive and normative implications," *American economic review*, 2019, *109* (7), 2383–2424.

Giannone, Elisa, Qi Li, Nuno Paixao, and Xinle Pang, "Unpacking Moving," Working Paper 2019.

Glazer, Amihai and Kai A. Konrad, "A Signaling Explanation for Charity," *The American Economic Review*, 1996, *86* (4), 1019–1028.

Guren, Adam M, Alisdair McKay, Emi Nakamura, and Jón Steinsson, "Housing Wealth Effects: The Long View," *The Review of Economic Studies*, 04 2020.

Heffetz, Ori, "A test of conspicuous consumption: Visibility and income elasticities," *Review of Economics and Statistics*, 2011, *93* (4), 1101–1117.

Jones, Charles I. and Peter J. Klenow, "Beyond GDP? Welfare across Countries and Time," *American Economic Review*, September 2016, *106* (9), 2426–57.

Krueger, Dirk and Fabrizio Perri, "Does income inequality lead to consumption inequality? Evidence and theory," *The Review of Economic Studies*, 2006, *73* (1), 163–193.

Massey, Douglas S., Jonathan Rothwell, and Thurston Domina, "The Changing Bases of Segregation in the United States," *The ANNALS of the American Academy of Political and Social Science*, 2009, *626* (1), 74–90.

Olafsson, Arna and Michaela Pagel, "The Liquid Hand-to-Mouth: Evidence from Personal Finance Management Software," *The Review of Financial Studies*, 04 2018, *31* (11), 4398–4446.

Phillips, David, "Measuring Housing Stability with Consumer Reference Data," 2019.

Qian, Franklin and Rose Tan, "The Effects of High-skilled Firm Entry on Incumbent Residents," 2020.

Reardon, Sean F and Glenn Firebaugh, "Measures of multigroup segregation," *Sociological methodology*, 2002, *32* (1), 33–67.

_ **and Kendra Bischoff**, "Income inequality and income segregation," *American Journal of Sociology*, 2011, *116* (4), 1092–1153.

_ **, Glenn Firebaugh, David O'Sullivan, and Stephen Matthews**, "A new approach to measuring socio-spatial economic segregation," in "29th general conference of the International Association for Research in Income and Wealth, Joensuu, Finland" 2006.

Theloudis, Alexandros, "Consumption inequality across heterogeneous families," Working Paper 2020.

Trounstine, Jessica, *Segregation by Design: Local Politics and Inequality in American Cities*, Cambridge University Press, 2018.

Veblen, Thorstein, *The theory of the leisure class: An economic study of institutions*, Aakar Books, 1899.

Appendices

A Data Appendix

A.1 Data Sources

In this section, we describe in further detail the rest of the data sources we use. We first give a broad overview of the ACS and the Nielsen Homescan datasets. We also provide more detail on the structure of the Infutor data and the variables we use to measure housing and car consumption segregation. Finally, we explain our imputation procedure for car and house prices and provide additional detail on the the geographic crosswalk.

A.1.1 American Community Survey

The ACS is an annual survey conducted by the Census Bureau since 2003 where individuals are randomly sampled in each state, the District of Columbia and Puerto Rico. We use information on income, education, age, race and geography (PUMA and state) from the ACS for two reasons. First, we use all the information above to validate the representativeness of the Infutor data. Second, we use information on race and income to measure residential segregation by race, by income, by age and by education, all of which are important variables in our analysis but are imputed in the Infutor data. We restrict the ACS sample to individuals between 22 and 80 and exclude observations with non-positive income. The income variable we focus on is total household income. Although the car and home characteristics data from Infutor is at the level of a car-individual owner or home-individual owner level, we view these two consumption categories as likely to be used jointly by all members of a household.

Although the ACS is available since the year 2000 we exclude the years before 2005 as the publicly available data does not report individuals' location besides the state of residence. In all our analysis we use the finest unit of geography available in the ACS, which is the Public Use Microdata Area (PUMA). There are 2,351 different PUMAs covering all the U.S. territory and they are state-specific, which means that PUMAs do not cross state borders.

The main ACS variables we use in the analysis are: total household income (`HHINCOME`) and house value (`VALUEH`). Our results for income segregation are robust to considering alternative income variables such as total personal earned income (`INCEARN`) or total personal income (`INCTOT`).

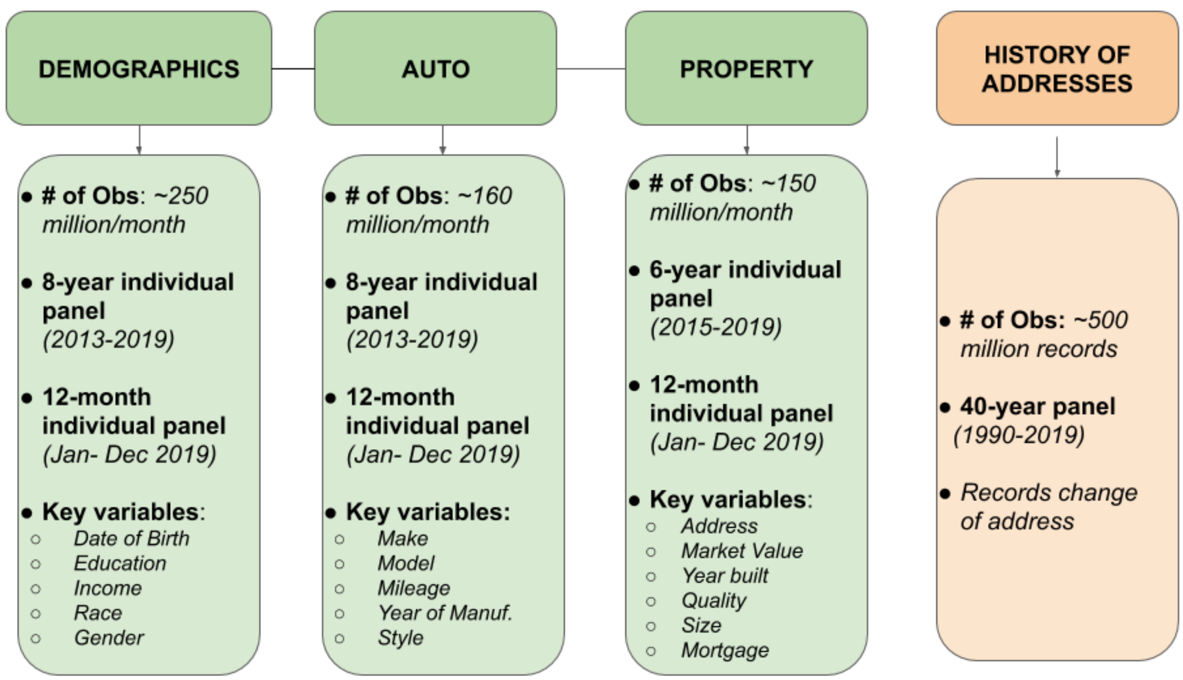
A.1.2 Census

To complement the ACS we use the 5% microdata sample from the 1990 and 2000 Census available in IPUMS. This samples contains information on approximately 10 million individuals and 5 million households. As with the ACS, from the Census we use in the analysis information on total household income and the house value.

A.1.3 Infutor

The Infutor data is organized as described in Figure 4. Here we supplement the description of the dataset from the main text with additional details.

Figure 4: Structure of Infutor Data



Notes: This figure describes the structure of the Infutor data divided in four main files. The first three files (Demographic Profiles, Auto Profiles and Property Profiles) have been linked through individual identifiers.

For both housing and vehicles we observe in the dataset the ZIP code where the house or the vehicle is located. ZIP codes are more than 10 times more disaggregated than PUMAs. However, given that our analysis for income is done at the PUMA level we aggregate ZIP codes to PUMAs, which we use as the finest geographic aggregation level for all the analysis, i.e. the geographic unit i in equation (1). Our segregation results for housing and vehicles are qualitatively robust to considering alternative definitions of the geographic unit i, such as ZIP codes or counties, instead of PUMAs. In Section A.4 we describe the ZIP-PUMA crosswalk we use to assign the ZIP codes in the Infutor data to PUMAs.

Housing. For each property we observe a unique identifier (given by the property address), an owner unique identifier, its location, its characteristics, such as the year of construction (`PROP_YRBLD`) or the number of rooms, information about the property deed, and its history of mortgages. Infutor also reports whether the property is used as a business or as a residence. For all our analysis we restrict to properties that are used for residential purposes only.

For houses we mostly rely on the deed data from which we observe information of the date (`PROP_SALEDATE`) and the price (`PROP_SALEAMT`) at which the property was acquired by the current owner in a given snapshot. Furthermore, for approximately 68% of the deed records we also observe these two variables for the previous deed of the property (`PROP_SALEDATE_PRIOR` and `PROP_SALEAMT_PRIOR`). Combined with the multiple snapshots of the data, this implies that for several properties we observe more than one transaction. On average we observe 1.86 transactions per property with a maximum of 7 transactions for some of the properties.

Sample selection. Using the variables described above, we include a house in the year t sample if:

$$\min\left\{\texttt{PROP\_YRBLD}, \min_{\text{snapshot}}\left\{\texttt{PROP\_SALEDATE\_PRIOR}, \texttt{PROP\_SALEDATE}\right\}\right\} \leq t, \tag{7}$$

where all the date variables are in years and the minimum is computed allowing for possible missing values. This definition implies that we include in our sample all the properties which we can verify that have been built or sold at any previous, or current, date. In Section A.2 we explain how we interpolate selling prices to compute the value of all in-sample houses across time.

Vehicles. For vehicles we observe unique owner-vehicle identifier together with the owner's address which allows us to identify vehicles' location. Unlike houses, we cannot track the same vehicle across multiple owners. We also observe relevant characteristics of the vehicle such as the manufacturer (`MAKE`), the model (`MODEL`), the year (`YEAR`), and the first 10-digits of the Vehicle Identification Number (`VIN`). For example, an entry in our data is a BMW-5 Series-2015 with VIN code WBA5M6C5xF.

As with housing, we combine all the information available at the different snapshots. This allows us to increase the number of vehicles across time, particularly as the coverage significantly increased in the most recent snapshots. Regarding the vehicle location, for the years between 2012 to 2018 we compute the segregation index using the current snapshot ZIP code, when available. For the rest of the years prior the first time we observe a vehicle we impute the ZIP code of the first snapshot in which we observe it. This assumption is likely to only have limited impact as between 2012 and 2018 on average only 3.3% of vehicles changed PUMAs and only 1.1% changed state.

Sample selection. A vehicle is included in the year t sample if

$$\texttt{YEAR} \leq t \leq \max\left\{\text{snapshot}\right\}, \tag{8}$$

where the max operator is computed across, potentially different snapshot years for which we observe the same vehicle.

Two comments about the vehicle sample selection are in order. First, the backward looking nature of equation (8), going back to vehicle's manufacturing year, allows us to run our segregation analysis even for years before Infutor's first snapshot, which corresponds to the year 2012 for the case of vehicles. Thus, for example, if we observe a Toyota-Corolla-2007 in the 2014 snapshot we include this vehicle in our segregation analysis starting from the year 2007 even though we observe this vehicle for the first time in 2014. In other words, what definitions (7) and (8) are doing is to include houses and vehicles since the first year we verify that they exist. Second, definition (8) allows for vehicle exit given by the last snapshot in which the vehicle was observed. We allow for that as for the cases in which Infutor confirmed that the vehicle was sold the owner-vehicle entry will stop appearing in the data in all subsequent snapshots. In Section A.3 we describe the detail of how we obtain the value of the vehicles in our sample and across time.

To test the validity of our vehicles' dataset, we exploit information on age and manufacturers. Specifically, the top panel of Table 12 reports the average age of vehicles in Infutor and BTS between 2012 and 2018. The average age in Infutor is slightly higher but both can be approximated to be at 12 years. The table also reports the correlation at state level of the average age. We find this correlation to be 0.54. The central (bottom) panel reports the age of vehicles in Infutor and NHTS in 2009 (2017). We find that the average age is 2 years higher (3 years lower) in NHTS than in Infutor and the state-level correlation to be 0.37 (0.33). We also analyze the distribution of make in both datasets. We find that overall the distributions are very similar both at national- and state-level. Table 13 reports the average age of vehicles at national level for each year and the BTS datasets and in both version of the Infutor datasets that we built. Overall we find that comparing the snapshop Infutor dataset to the BTS, the latter has on average slightly younger vehicles. Instead, when we compare the baseline dataset to the BTS, we find that the latter has slightly older cars for the years before 2016 and it reverts afterwards. Overall, the differences are not very large.

A.1.4 Nielsen Homescan

For non-durable consumption we use the Nielsen Homescan Data from the Kilts Marketing Data Center at the University of Chicago Booth School of Business. These data consist on a longitudinal panel of approximately 40,000-60,000 U.S. households and contain information about the products they buy, as well as when and where they were purchased between 2004 and 2017. It tracks consumers' grocery purchases by asking them to scan the bar codes for each product they purchase after each shopping trip. The Nielsen Homescan data has national coverage and provides wide variation in household location and demographics. Overall, the data include purchases of almost 250 million different items. One of the advantages of this dataset is that it records the bar codes at a very fine level, as well as the expenditure on each of them. Moreover, it covers longer period of time than Infutor. A disadvantage of the Nielsen Homescan dataset relative to the Infutor data is that the sample is orders of magnitude smaller, which means that we would not be able to use these data at very fine geographical detail.

The Nielsen-Kilts data reports detailed location of households. In particular it reports households' ZIP code of residence. We use the same crosswalk used for the Infutor data to assign households to the different PUMAs.

Household purchases are reported at a very granular level. Specifically, at the Universal Product Code (UPC) level. This data reports both the quantity and the total expenses made at the UPC level. Besides UPC there are other two additional aggregation levels which are product modules, such as soap or beer, and ten different department codes such as dairy or health and beauty consumption.

A.2 House Prices

This section explains how we compute prices for in-sample houses in the Infutor data, defined in equation (7), at any time t. We use observed selling prices to compute ZIP code level price indices with which we interpolate property prices at different time periods.

In our analysis we restrict attention to properties for which we observe the date and the price of at least one transaction. As explained above, for each property we keep all the selling

Table 12: Representativeness in Infutor and BTS datasets

		National-level			State-level	
		BTS	NHTS	Infutor	FHA	NHTS
2012-2018						
Vehicle Age						
	Mean	11.5		12.2		0.54
2009						
Vehicle Age						
	Mean	10.3	9.4	7.1		0.37
Vehicle Make*						
	Chrysler		0.12	0.15		0.74
	Ford		0.19	0.19		0.59
	GM		0.22	0.22		0.62
	Honda		0.09	0.08		0.40
	Toyota		0.12	0.10		0.22
	Other		0.26	0.26		0.36
N		254,582,694	211,501,318	98,996,193	0.32	0.44
2017						
Vehicle Age						
	Mean	11.7	10.4	13.3		0.33
Vehicle Make*						
	Chrysler		0.11	0.13		0.71
	Ford		0.15	0.18		0.65
	GM		0.19	0.22		0.73
	Honda		0.11	0.08		0.57
	Toyota		0.15	0.11		0.40
	Other		0.30	0.28		0.55
N		254,582,694	222,578,947	158,898,357	0.56	0.54

Notes: This table reports the mean of cars' age for the different periods and datasets in our sample. For year 2009 and 2017, it also reports the distribution of cars' makes.

Table 13: Age distribution of cars in Infutor and BTS

	National-level		
Vehicle Age	BTS	Snapshot	Baseline
2000	8.9		5.7
2001	8.9		5.9
2002	9.6		6.0
2003	9.7		6.1
2004	9.8		6.3
2005	9.8		6.6
2006	9.9		6.9
2007	10		7.2
2008	10.1		7.4
2009	10.3		8.0
2010	10.6		8.4
2011	10.9		8.8
2012	11.2	9.7	9.1
2013	11.4	12.0	9.5
2014	11.4	11.6	10.2
2015	11.5	12.1	10.9
2016	11.6	12.4	11.7
2017	11.7	13.3	12.6
2018	11.7	14.4	13.5
Corr BTS			
2012-2018		0.950	0.952
2000-2018			0.935

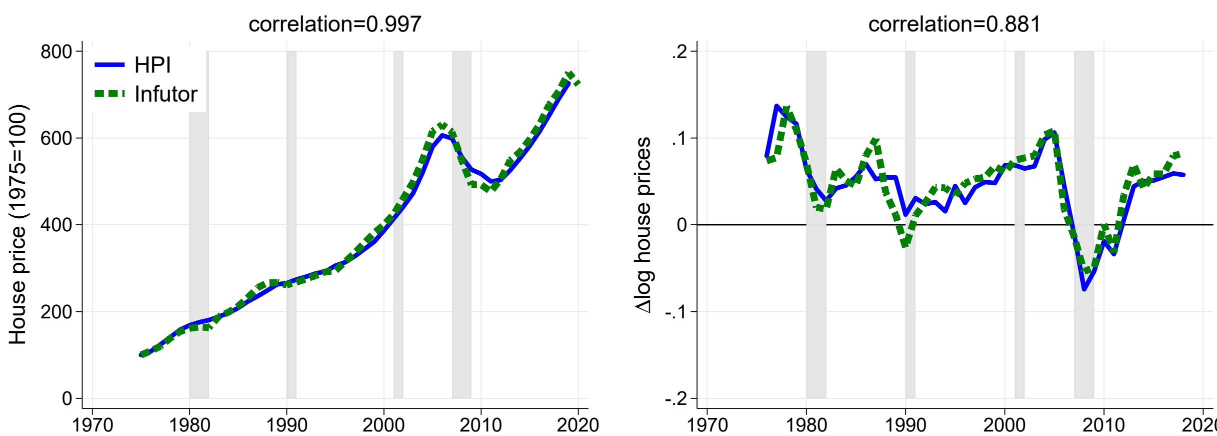
Notes: This table reports the age distribution of cars in BTS and Infutor. For Infutor, we report both datasets, specifically, the "Snapshot" and the "Baseline" version. The bottom of the table reports the correlations for the time series above.

dates and prices available in the data. The total number of transactions we observe varies by year. For example, for the years before 1990 we observe around 600,000 annual transactions. For the time period between 1990 and 2018 we observe more than 3 million transactions per year.

Using the selling prices we compute a time series for the median transacted house price at different geographies: at the national, state, PUMA and ZIP code level. To asses the quality of our house price data, Figure 5 displays the level and the annual log changes of the national-level median price against the House Price Index (HPI) from the Federal Housing Finance Agency. This figure shows that the national-level house prices obtained from Infutor are consistent with aggregate-level house price dynamics and properly capture the different boom and bust episodes observed in the last four decades.

Figure 5: House Prices

(a) Total consumption (b) Durable consumption



Notes: HPI denotes the All-Transactions House Price Index from the Federal Housing Finance Agency. Infutor denotes the national-level median selling price.

ZIP Code House Price Indices. We use the data to construct ZIP code level price indices from 1950 to 2018. To that end, we first compute annual price changes across all the four geographies for which we observe at least 50 transactions. If this constraint is not met for a given ZIP-year pair we try to use the price change of the immediate broader unit of geography level, which is the PUMA. If the corresponding PUMA-year does not have the price change available we continue to the state or even the national-level. These imputations are more common as we go back in time, particularly, before 1990.

Price Interpolation. With the corresponding ZIP code level price index in which the property is located we interpolate prices to other years different from the property observed transactions. This strategy takes into account different boom and bust house price cycles observed at different geographies. To exemplify our interpolation strategy, suppose that we observe that house h, located in ZIP code z, was sold at price $p_{h,z,\tau}$ in period τ. We compute the price of house h at any other year t by assuming that its price between period t and τ followed the zip code level price dynamics. This assumption can be written as

$$\Delta_{t-\tau} \log p_{h,z,\tau} = \Delta_{t-\tau} \log p_{z,\tau},$$

which implies that house h price at year t is equal to

$$p_{h,z,t} = \exp\left(\log p_{h,z,\tau} + \Delta_{t-\tau} \log \log p_{z,\tau}\right),$$

where $p_{z,\tau}$ is ZIP code z price index in period τ.

Note that in the expression above we could have $t < \tau$ as long as equation (7) is satisfied. For the properties for which we observe more than one transaction we interpolate the price at period t using the closet (in terms of minimum time distance) selling price.

A.3 Vehicle Prices

One limitation of the Infutor vehicle data is that we do not observe prices or any other estimate for the value of vehicles. To circumvent this limitation we merged the Infutor data with transaction prices for all the dealer sales of new and used cars in Texas from 2012 to 2019. Dealer sales refers to all the sales done by licensed dealers.

We perform this merge in two steps, trying to use the most disaggregated data available. To that end, we first compute time series for 10-digit VIN-level mean selling prices for all the VINs for which we observe at least 50 transactions. Additionally, we compute mean selling prices, also restricting to the minimum 50 observations constraint, for all the make-model-year combinations. VIN codes are considerably narrower specifications compared to make-model-year tuples as they also distinguish other technical characteristics such as the vehicle engine or the type of fuel it uses. To put this in perspective, in Infutor, we observe more than 130,000 different 10-digit VINs and close to 15,000 make-model-year combinations. In our data around 50% of the make-model-year tuples have at most 4 different 10-digit VINs.

Using both sets of time series we compute VIN-level prices for 2012 to 2018. As we did for houses, we impute missing VIN-level prices using the make-model-year price when the VIN-level price is not available. For these years we drop observations below the 10^{th} and above the 90^{th} percentile annual price change distribution. This restriction rules out, for example, price increases in used cars, which probably reflect changes in the composition of sold vehicles across time.

Using prices from 2012 to 2018, we then interpolate prices for missing observations and for the years before 2012, for the older vehicles in our sample. For that we use a VIN-level annual depreciation rate. Specifically, for each VIN v we compute the average depreciation rate between 2012 and 2018 as

$$\delta_v = -\frac{1}{\#\mathcal{T}_v} \sum_{t \in \mathcal{T}_v} \Delta \log p_{v,t},$$

where $\mathcal{T}_v \subset \{2012, \ldots, 2018\}$ is the set of years for which we observe VIN v's prices. The average depreciation rate (or average annual price decrease) in our VIN-level prices is 0.108.

With this VIN-level depreciation rate we interpolate missing prices for our in-sample vehicles in year t that satisfy equation (8). For example, for a 2005 VIN ($\texttt{YEAR}= 2005$) for which we observe selling prices starting in 2012 we compute its time $2005 \leq t < 2012$ price as

$$p_{v,t} = \exp\left[\ \log p_{v,2012} + (2012 - t)\delta_v\ \right],$$

where $p_{v,2012}$ is the VIN-level selling price observed in 2012.

A.4 Geographic Crosswalks

In addition to the country and U.S. states, the economic geography and segregation literature usually considers five other levels of geography: (1) ZIP-code, (2) county, (3) Public Use Microdata Area (PUMA), (4) Core Based Statistical Area (CBSA), and (5) Commuting Zone (CZ). These categories are presented in Table 14, ordered from left to right in terms of their level of disaggregation.

We make some remarks about these units of geography. First, ZIP-codes do not cover the entire territory, approximately 0.002% of population is not assigned to a ZIP-code. Additionally, a ZIP-code can cover more than one state. Second, counties cover the entire territory and are state-specific. Third, PUMAs also cover the entire territory and are state-specific. As mentioned above, this is the finest aggregation level available in the ACS and Census public use microdata. Fourth, CBSAs do not cover the entire territory, approximately 6% of population is not assigned to a CBSA. CBSAs can cover more than one state. For example, the CBSA New York-Newark-Jersey City, spans three states: New York, New Jersey and

Table 14: Number of Locations by Geographic Aggregation Level

	ZIP	County-10	PUMA	CBSA-15	CZ
MCDC	32,845	3,143	2,351	933	741
ACS [2005-2018]		376-430	2,351		
Census 1990		385	1,726		
Census 2000		377	2,351		
Infutor [2012-2019]	39,131				

Notes: MCDC denoes the Missouri Census Data Center. County-10 and CBSA-15 denote the list of counties and CBSAs in 2010 and 2015 respectively. The Missouri Census Data Center Geographic Correspondence Engine is a comprehensive source of definitions and geographical cross-walks available for the United States.

Pennsylvania. Fifth, MSAs (not reported in the table), are, broadly, a subgroup of CBSAs that only restricts to metropolitan areas. There are 384 MSAs (vs. 933 CBSAs). Lastly, CZs are clusters of U.S. counties that are characterized by strong within-cluster and weak between-cluster commuting ties.

For our analysis we constructed a crosswalk that uniquely assigns ZIPs to PUMAs (an injection correspondence), and consequently, to states. We started from the ZIP-PUMA crosswalk available in the MCDC. This crosswalk, besides assigning ZIPs to PUMAS, reports the ZIP-code population share that is assigned to the potentially different PUMAs. Indeed, for approximately 28% of the ZIP-codes there is more than one PUMA assigned. In these cases we assigned each ZIP to a single PUMA using the one with the largest population share. For example, if a ZIP-code is assigned to two PUMAs with 70-30% population shares we assigned this ZIP-code to the former PUMA that has a 70% population share. With this procedure we constructed an injective crosswalk between ZIP codes to PUMAs. This crosswalk is available upon request.

B Robustness

This section investigates robustness with respect defining the entropy index at CBSA level rather than at state level. We also report the correlation coefficients between entropy indices at national or state level calculated using zipcodes, counties and PUMAs as the underlying geographic unit. Table 15 suggests that the correlations between the entropy indexes for car and housing consumption when the smallest unit of geography is the zipcode, county or PUMA are very highly correlated both at national level and at state level. The correlations range between 0.639 and 1.

Table 15: Correlations between Entropy Indexes at Different Levels of Geography

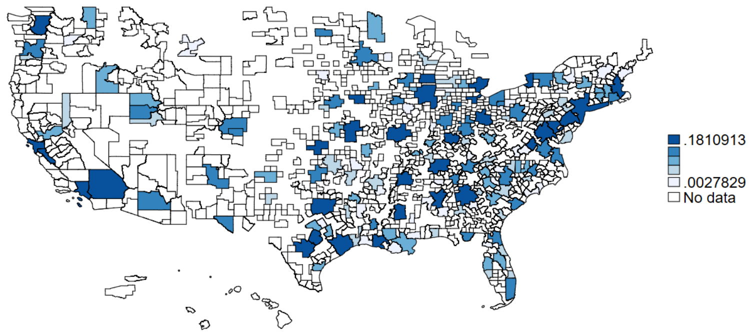
	State-level		National-level	
	Housing - PUMA	Car - PUMA	Housing - PUMA	Car - PUMA
Housing - County	0.717***		0.971***	
Housing - Zipcode	0.971***		0.976***	
Car - County		0.812***		1.000***
Car - Zipcode		0.639***		0.992***
Observations	2499	1224	49	24

Notes: This table reports the correlations between H-indexes for housing and car consumption measured using the Infutor data for different levels of underlying geographies. On the left panel we report correlations between H-indexes aggregated at national level. On the right, we report correlations for H-indexes aggregated at state-level.

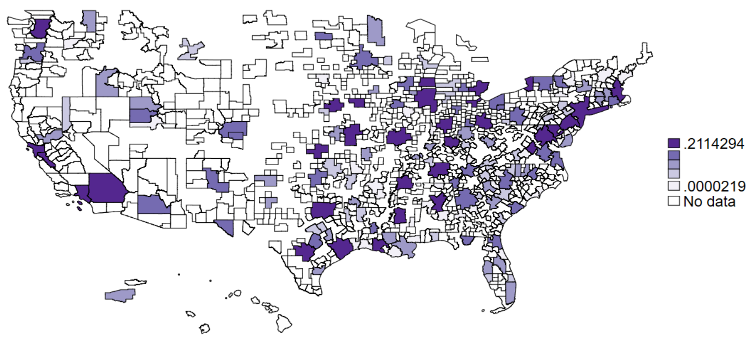
B.1 Entropy Index for CBSAs

Figure 6: CBSA-level Consumption Segregation

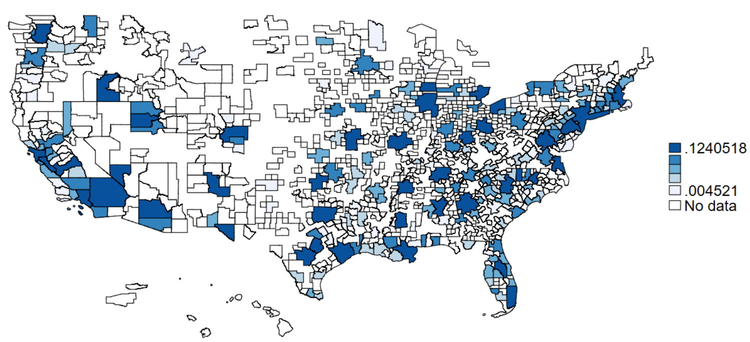
(a) Total consumption



(b) Durable consumption



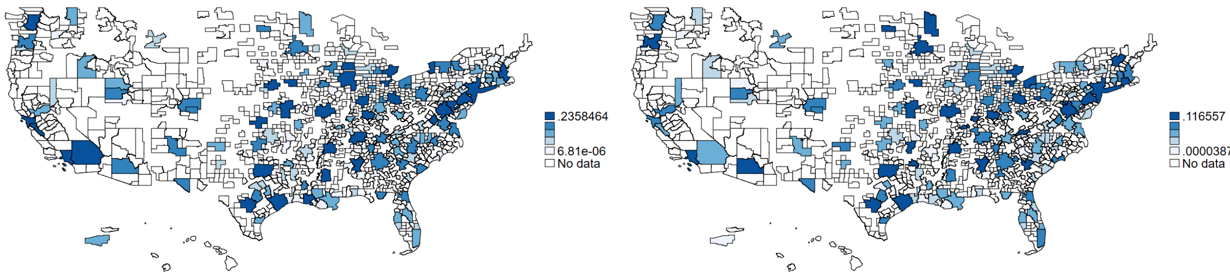
(c) Non-durable consumption



Notes: The figure plots CBSA-level consumption entropy indices averaged over the period 2016-2018.

Figure 7: CBSA-level Durable Consumption Segregation

(a) Housing (b) Cars



Notes: The figure plots CBSA-level consumption entropy indices averaged over the period 2016-2018.

Table 16: Consumption Segregation and Regional Characteristics

	Total consumption	Durable consumption	Non-durable consumption
	By income		
Bottom 25%	0.096	0.107	0.067
Top 25%	0.200	0.251	0.085
	By education (college share)		
Bottom 25%	0.101	0.113	0.068
Top 25%	0.188	0.236	0.072
	By race (share white)		
Bottom 25%	0.200	0.246	0.085
Top 25%	0.098	0.115	0.056
	By age (share $\leq$ 35)		
Bottom 25%	0.118	0.141	0.060
Top 25%	0.172	0.207	0.089
	By population		
Bottom 25%	0.061	0.068	0.044
Top 25%	0.169	0.206	0.078

Notes: The table reports population weighted averages of state-level consumption entropy indices over the period 2016-2018.

Table 17: Consumption Segregation by Demographic Group

	Total consumption	Durable consumption	Non-durable consumption
		By race	
White	0.143	0.166	0.083
Black	0.156	0.170	0.118
Other	0.152	0.183	0.070
		By education	
No college degree	0.148	0.168	0.095
College degree	0.166	0.178	0.135
		By age	
Younger than 35	0.167	0.184	0.123
Older than 35	0.148	0.176	0.076

Notes: The table reports population weighted averages of state-level consumption entropy indices over the period 2016-2018.

Table 18: Drivers of Consumption Segregation at State Level

	Total consumption			Durable consumption			Non-durable consumption		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$\ln H_Y$	0.60***	0.49***	0.47***	0.77***	0.65***	0.49***	0.20***	0.25***	0.21**
	(0.05)	(0.06)	(0.08)	(0.05)	(0.06)	(0.09)	(0.06)	(0.07)	(0.09)
$\ln H_R$		0.14***	0.14*		0.16***	0.14**		-0.06	-0.07
		(0.07)	(0.08)		(0.06)	(0.07)		(0.05)	(0.06)
$\ln H_E$			0.04			0.22**			0.07
			(0.12)			(0.11)			(0.09)
$\ln H_A$			-0.05			-0.08			-0.02
			(0.05)			(0.05)			(0.07)
R^2	0.82	0.84	0.84	0.79	0.81	0.82	0.53	0.53	0.53

Note: The table reports the estimates of α_1, α_2, α_3 and α_4 in equation (6). The estimate of α_0, the time fixed effects and the estimate of the vector $\boldsymbol{\gamma}$ are omitted. Robust standard errors are reported in parentheses. The regression is estimated with population weights based on the 2010 Census. ***, **, and *, represent statistical significance at 1%, 5% and 10%, respectively.

Table 19: Consumption and Income Segregation, State Level

	Total	Between	Within
Total consumption	2.05	0.04	2.01
α_1^i/α_1		2%	98%
Non-durable consumption	0.71	0.25	0.47
α_1^i/α_1		35.2%	64.8%
Durable Consumption	2.99	0.15	2.84
α_1^i/α_1		5%	95%
Cars	0.14	0.02	0.12
α_1^i/α_1		14.3%	85.7%
Housing	3.34	0.13	3.21
α_1^i/α_1		3.9%	96.1%

Notes: The table reports the estimates of α_1, α_1^B and α_1^W. All estimates are significant at 1% significance. Robust standard errors, time fixed effects and the estimates of $\boldsymbol{\gamma^i}$ and $\boldsymbol{\gamma}$ are omitted but are included in the estimation. The regression is estimated with population weights based on the 2010 Census, using data for the 2016-2018 period.