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Residential Demographic Multipliers: Using Public Use Microdata Sample Records To Estimate Housing Development Impacts

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Abstract

Impact analysis plays a critical role in evaluating development proposals, devising housing policies, and developing comprehensive plans. To assess how enrollment and population increase and how net fiscal impacts affect municipalities and school districts, analysts require the latest evidence-based demographic multipliers that are specific to housing types. However, because outdated statewide multipliers are still widely used, an urgent need exists to devise up-to-date demographic multipliers to reduce imprecise impact assessment. In this article, we discuss a new generation of demographic multipliers based on the latest annually released American Community Survey

Abstract (continued)

(ACS) Public Use Microdata Sample (PUMS). We introduce a larger and more stable sample of households that have recently moved into both new and old housing units. We believe that these new multipliers are more accurate and relevant to impact assessment. With improved methodology, we can make these multipliers more geographically specific. Finally, we discuss the challenges and the new direction in using ACS PUMS data to generate statistically valid multipliers in small geographical units.

Introduction

This article discusses the methodology used to update and revise outmoded demographic multipliers. It first provides a background of traditional multipliers developed from the discontinued U.S. Census Bureau Public Use Microdata Sample (PUMS) records. It then summarizes procedures for using current American Community Survey (ACS) PUMS to generate updated multipliers. After introducing an improved mover sample, the article discusses recent demographic changes and other means to resolve the insufficient sample size problem prevalent in traditional multipliers and also discusses potentials for small-area multipliers.

Residential Demographic Multiplier and Its Data Sources

A residential demographic multiplier is an average ratio of demographic measures per occupied housing unit or per household.[1] Commonly used multipliers include school-age children (between 5 and 17 years of age) and average household size. The demographic impact of a residential development depends on its housing mix defined by structure type (for example, single-family detached, townhome, multifamily), size (for example, one bedroom, two bedrooms, three bedrooms), and tenure (for example, renter- or owner-occupancy). Demographic multipliers serve a critical role in the fiscal impact studies that developers, school board members, local government officials, and policymakers rely on to make land use and zoning decisions.

Several data sources can be used to estimate the demographic multipliers. Summary data from the pretabulated tables in the decennial census or ACS can be used to estimate the average household size and presence of school-age children by dividing the total household population and the residents ages 5 to 17, respectively, by the number of households. However, this methodology does not differentiate structure types, sizes, and tenure. Furthermore, this method covers all occupied housing units without taking account of the time of construction or moving into the unit. Alternatively, planners and researchers can conduct local surveys of recent development to collect demographic data. Although these surveys allow for detailed housing differentiation, they can be expensive and time consuming. The results are reflective only of the development surveyed and not all recent developments.

[1] By definition, the number of households is identical to the number of occupied units. Any apparent difference is due to a slight sampling fluctuation.

A third source is PUMS, freely distributed by the Census Bureau. PUMS files contain the actual responses to questionnaires sent to a sample population. Through the early 2000s, PUMS was released every 10 years; since the mid-2000s, PUMS is reported every year under the ACS.[2] PUMS covers the full range of population and housing unit responses, collected on individual questionnaires, for a subsample of housing units and group quarters. By combining data on the housing unit (housing records) and on the household and individuals who live in the unit (person records), researchers can generate demographic multipliers for specific housing household groups. PUMS is the major data source that Burchell and Listokin (1978) used in their pioneering work of generating demographic multipliers.

Burchell and Listokin (1978) reported demographic multipliers for 19 types of housing configurations under nine regional subdivisions. A configuration is a category in a housing typology defined by housing characteristics, such as structure, size (bedrooms), housing tenure, and housing value. Their analysis was restricted to a sample of units built within the past 10 years. Following their initial work, Burchell and Listokin improved their estimation methodology and reported multipliers based on contemporaneous census PUMS and American Housing Survey data (Burchell, Listokin, and Dolphin, 1994, 1985).

The 2000 Census PUMS-Derived Multipliers

Burchell, Listokin, and Dolphin (2006) updated their methodology using data from the 2000 census 5-percent PUMS. The multipliers reported the average household size and the presence of school-age children and public school-age children in 19 broad housing configurations that were further categorized into four groups by housing rent or value (exhibit 1). These sets of multipliers—commonly referred as the Fannie Mae multiplier series—covered Washington, D.C., and 50 states.

Listokin et al. (2006) generated multipliers in a slightly different manner, of only New Jersey and its three substate regions. They addressed a variety of issues in using the 2000 census PUMS, including the duration of the data, determinants of multipliers, research results on specialized housing, and the applications of multipliers in fiscal impact analysis and impact fee estimations.

Exhibit 1

Broad Housing Configurations in the Fannie Mae Multiplier Series

Number of Bedrooms	Single-Family Detached	Single-Family Attached	5+ Units Owner	5+ Units Renter	2–4 Units	Mobile
1			✓	✓	✓	
2	✓	✓	✓	✓	✓	✓
3	✓	✓	✓	✓	✓	✓
4	✓	✓				✓
5	✓					

Source: Burchell, Listokin, and Dolphin (2006)

[2] Through 2000, PUMS used responses to the long-form questionnaires in the decennial census. Since the mid-2000s, the Census Bureau has distributed a survey each year under the ACS to about 1 percent of the population. The responses are reported in ACS 1-year, 3-year, or 5-year PUMS files.

The work of Burchell and Listokin has not been updated since 2006. To assess the impact of new housing developments, policy analysts need the most accurate and current data. The use of outdated data can produce inaccurate estimates of development impacts, overestimating or underestimating how new developments will impact schools, traffic patterns, and municipal finances. Despite the need for multipliers that reflect up-to-date demographic trends and local conditions, decades-old statewide multipliers are routinely used. In the next section, we detail the procedures that employ the latest ACS PUMS records to generate multipliers.

Methodology of Statewide Multipliers Using ACS 5-Year PUMS

In response to the lack of updated demographic multipliers, Wong (2005) independently generated multipliers from 2000 census PUMS data for several Public Use Microdata Area (PUMA) aggregates.[3] In early 2016, the Community Data Analytics (CDA) team formed to update the multipliers using the most recent data. The following discussion is of the four major steps in generating statewide multipliers based on ACS 5-year PUMS: (1) select records, (2) create housing configurations, (3) populate observations, and (4) calculate the multipliers. These steps pertain to a sample of recently built units. A subsequent discussion on other samples and PUMA or county-level multipliers will follow.

Step 1: PUMS Record Selection

The first step is to download and combine the ACS PUMS housing and person records for the state in question. The variable *YBL* (year structure first built) is employed to create the recently built unit sample for households living in structures built within 10 years prior to the ending year of the ACS 5-year PUMS (exhibit 2).

Exhibit 2

Common PUMS Variables Used in Multiplier Estimation

PUMS Variable	Explanation
ADJHSG	Adjustment factor for housing dollar amounts
AGEP	Age
BDSP	Number of bedrooms
BLD	Units in structure
GRNTP	Gross rent (monthly amount)
MV	When the householder moved into house or apartment
SCHG	Grade level attending
TEN	Tenure
VALP	Property value
YBL	When structure first built

PUMS = Public Use Microdata Sample.
Source: 2011–2015 American Community Survey PUMS Data Dictionary

[3] A PUMA is a statistical area defined as a substate unit containing at least 100,000 persons. It is built on contiguous census tracts within a state, and it may cut across counties. In practice, some PUMAs have more than 200,000 persons. For example, the most populous PUMA (0500 in Florida) has a 2010 population of 268,718.

Step 2: Housing Configuration Creation

Multipliers are specific to housing configurations, so several PUMS variables are required to establish a contingency table. On a basic level, two variables, *BLD* (units in structure) and *BDSP* (number of bedrooms) are used. Structure groups—single-family detached, single-family attached, and multifamily units—use *BLD* values. The multifamily group is usually classified further by number of units in the structure. *BDSP* is used to create size groups of the units such as studio, one to three-bedroom, and other size categories. Additional variables are added to refine the configurations. A common variable is *TEN* (housing tenure), used to differentiate owner- and renter-occupied units. Burchell, Listokin, and Dolphin (2006) and Listokin et al. (2006) used *VALP* (property value) and *GRNTP* (monthly gross rent) to classify units by the median or terciles of housing value and gross rent.[4] If these two variables are used, researchers should use *ADJHSG* (housing dollars adjustment factor) to inflate current dollars to constant dollars in the ending year of the ACS 5-year PUMS.

Step 3: Populate Records by Housing Configuration

This step assigns housing records and associated person records to each housing configuration. If all the variables discussed so far are used, the analysis is a five-way crosstabulation, including the filtering variable *YBL*. At this level, the probability of an insufficient sample for some configurations increases significantly, except in states with large populations.

Step 4: Multiplier Calculation

The next step estimates the weighted number of school-age children, occupants, and households for each housing configuration.[5] Because PUMS records are sample data, this step applies relevant replicate weights provided by PUMS to estimate weighted observations from unweighted observations.[6] Dividing the weighted number of school-age children and occupants by the weighted number of households yields the results of the multipliers. Following the Census Bureau standard of 90-percent confidence level, the margin of error is calculated. If age cohorts or grade groups are needed, additional variables like *AGEP* (age) and *SCHG* (grade level) are used to classify persons or school-age children according to major groupings.[7]

We used the preceding methodology and data from the 2000 census PUMS to replicate the New Jersey multipliers of Burchell, Listokin, and Dolphin (2006). We were able to successfully verify the demographic multiplier estimates. We completed statewide average household size and school-age children for all 50 states and selected PUMAs, including all Ohio PUMAs, using the 2011–2015 ACS PUMS. For quality control, CDA conducts several tests and examines the unweighted number of households to discard estimates without a sufficient sample size.

[4] Listokin et al. (2006) used a universal cap rate of 10 percent to convert gross rent to housing value. The authors recommended following the convention in their Fannie Mae multiplier series of not conducting such a conversion, because the cap rate varies across time and place.

[5] The discussion excludes two similar multipliers—public school-age children and public school children. As the public school participation rate varies among school districts, applying a statewide multiplier for local use results in biased impact estimations. The authors recommended not developing these two multipliers at the state level.

[6] The documentation for the replicate weight methodology is in ACS Variance Replicate Tables. See https://www.census.gov/programs-surveys/acs/technical-documentation/variance-tables.html.

[7] Such differentiation usually comes with a large margin of error in small states.

The Mover Sample Developed by CDA

The previously discussed procedures are based on a sample of recently built units. However, with a large share of records on older units removed, the variance of the demographic multiplier significantly increases in less-popular housing configurations. This insufficient sample size is further aggravated when recent housing construction is not active.

To resolve this sample size problem, CDA proposed an alternative sample that resembles the recently built unit sample. Based on the assumption that movers to new and older units have similar attributes as those who live in recently built units, CDA constructed a mover sample. The variable *MV* (when the householder moved into the unit) is used to identify households that moved in within 4 years of the starting year of the ACS 5-year PUMS.[8] Exhibit 3 summarizes the ratios between the estimated weighted numbers of households of both samples to all households and to one another. At the state level, the mover sample accounts for about 26 to 52 percent of all households, whereas the recently built unit sample represents about 3 to 16 percent. On average, the estimated number of households in the mover sample is 4.4 times larger than that of the recently built unit sample.

The mover sample improves the accuracy of the estimates and is less affected by housing activity. This sample also makes the estimation of local multipliers easier. The scatterplot of 362 pairs of average household size multipliers in exhibit 4 illustrates high correlation (Pearson *r* of 0.966) between the two samples.[9] The mover-based multipliers are more conservative; that is, less likely to underestimate impacts, except in some outlying five-bedroom configurations. Even if the assumption that movers to recently built units share similar characteristics with movers into older units is not completely true, the mover sample captures long-term characteristics of the future population when recently built units age. After all, a large share of recently built unit households is included in the mover sample.[10]

Exhibit 3

Comparing the Estimated Number of Households by Various Housing Configurations: 50 States and Washington, D.C.

	Recently Built Unit Sample	Mover Sample	
	Ratio of the Number of Households to All Households	Ratio of the Number of Households to All Households	Ratio of the Number of Households to That in the Recently Built Unit Sample
Minimum	0.03	0.26	2.61
Median	0.09	0.36	4.40
Maximum	0.16	0.52	11.18

Notes: The number of occupied units and households is identical by definition. Any apparent difference is due to a slight sampling fluctuation.
Sources: 2011–2015 American Community Survey (ACS) Table B25003; Community Data Analytics 2017 Planning Ratio Estimation Program computations derived from 2011–2015 ACS Public Use Microdata Sample

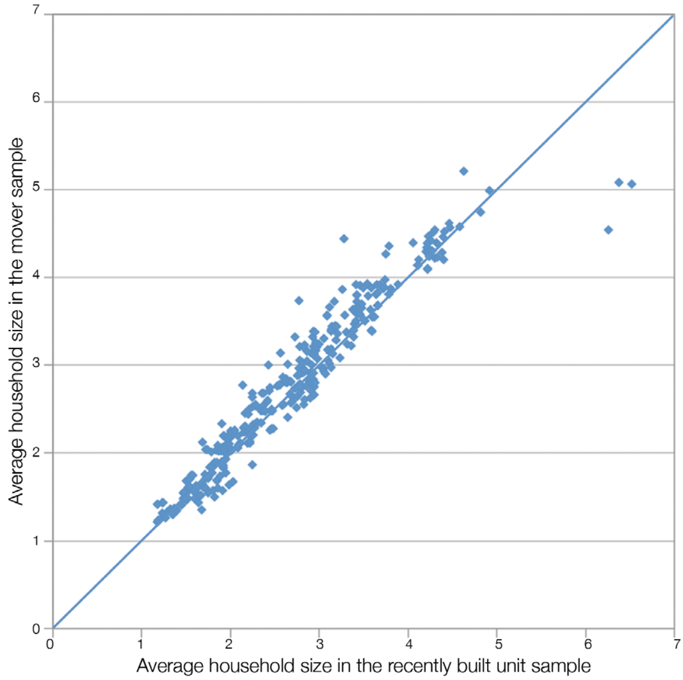
[8] For samples generated from the 2011–2015 ACS PUMS, the earliest move-in year in a mover sample is 2008. This sample contains all households in the recently built unit sample that moved into the unit between 2008 and 2015 but excludes those between 2006 and 2007.

[9] Because of overlapping sample elements and an unknown degree of heteroscedasticity, a statistical evaluation of individual pairs should be conducted. However, the rationale of using a mover is not statistical but practical, relying on an assumption that movers into new units are similar to other movers in the long run.

[10] The newly built unit sample generated from the 2011–2015 ACS PUMS covers units built between 2006 and 2015, and all units built between 2008 and 2015 are included in the mover sample.

Exhibit 4

Average Household Size Multipliers Between Two Samples—Arkansas, California, Georgia, New Jersey, and Ohio (362 Pairs by Various Housing Configurations)



Note: Excludes estimates with less than 30 unweighted observations in either sample.
Source: Community Data Analytics 2017 Planning Ratio Estimation Program computations derived from 2011–2015 American Community Survey Public Use Microdata Sample using both samples

In addition, more than one-third of the mover sample belongs to the recently built unit sample for places with active housing construction. In low housing-activity places, the recently built unit sample does not provide adequate information for refined housing configurations.

2000–2015 Demographic Changes

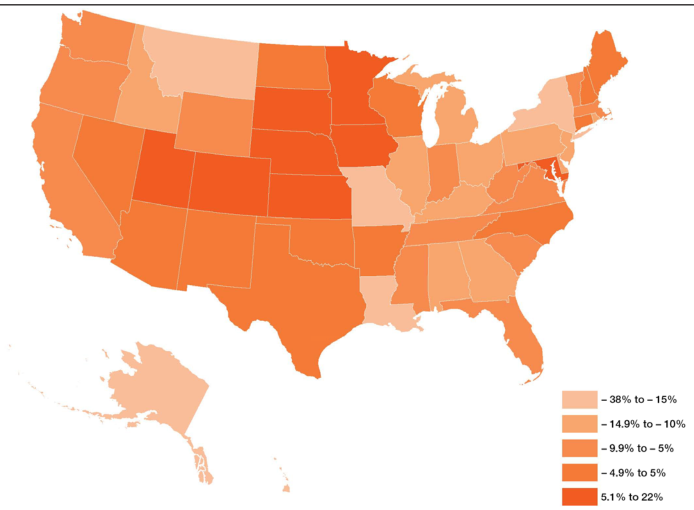
In this section, we highlight some major demographic changes as revealed by the CDA multipliers. First, in most states, the school-age children and average household size multipliers for most housing configurations declined between 2000 and 2015. This decrease is in line with the nationwide decline in average household size for all households.[11] Exhibit 5 illustrates changes in the number of school-age children for two-bedroom multifamily units between 2000 and 2015 and its decline in 39 states.

[11] Between 2000 and 2010, the average household size for all households fell or stagnated in every state except California, Delaware, Florida, Nevada, and Texas. Factors leading to the decline include falling fertility rates, an increase in single-person households (widowing or delay in marriage), aging of baby boomers, millennials choosing to delay parenthood, and the appeal of urban living. However, the direction and intensity of changes during this period is highly local.

Second, the use of a mover sample enables us to examine local variations of residential demographic multipliers. Exhibits 6 and 7 use the number of school-age children in Ohio to illustrate deviations between local (PUMA-level) and state estimates.

Exhibit 5

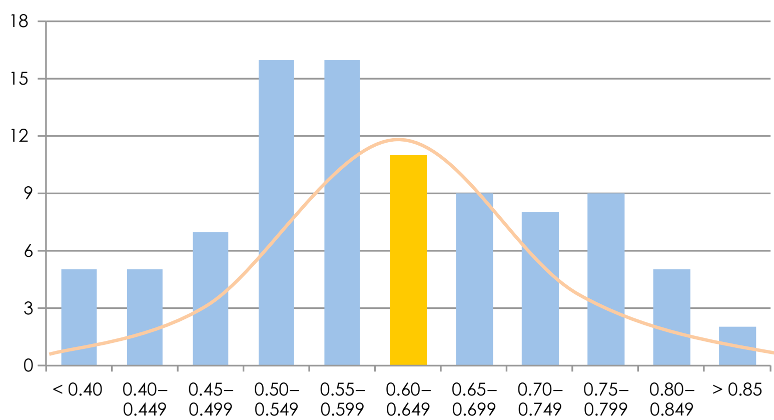
Percent Changes in School-Age Children Multiplier Between 2000 and 2015, Two-Bedroom Multifamily Units Using a Mover Sample



Source: Community Data Analytics 2017 Planning Ratio Estimation Program computations derived from 2000 Census Public Use Microdata Sample (PUMS) and 2011–2015 American Community Survey PUMS

Exhibit 6

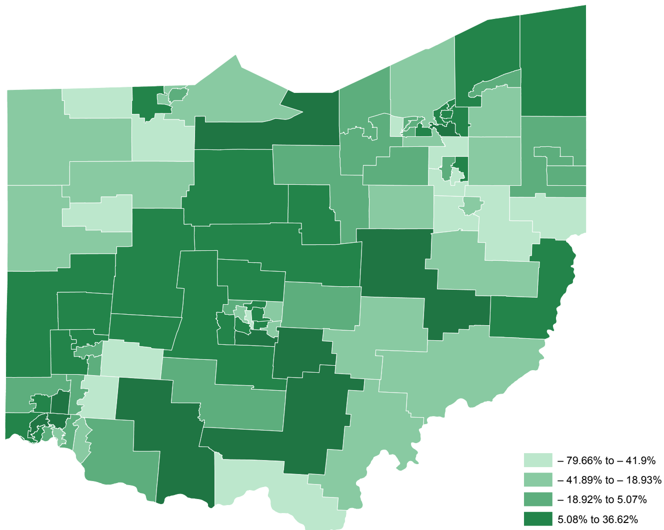
Distribution of School-Age Children Multipliers for Three-Bedroom, Single-Family Detached Dwellings: 93 Ohio PUMAs Using a Mover Sample



PUMA = Public Use Microdata Area.
Note: Statewide estimate at 0.63.
Source: Community Data Analytics 2017 Planning Ratio Estimation Program computations derived from 2011–2015 American Community Survey Public Use Microdata Sample

Exhibit 7

Deviation of School-Age Children Multipliers for Two-Bedroom, Multifamily Units From the State Estimate: 93 Ohio PUMAs Using a Mover Sample



PUMA = Public Use Microdata Area.
Source: Community Data Analytics 2017 Planning Ratio Estimation Program computations derived from 2011–2015 American Community Survey Public Use Microdata Sample

Multipliers for Small Geography

The key challenge to multipliers at the local level is an insufficient sample size. Although the use of a mover sample reduces variances, estimates at the PUMA level for highly differentiated housing configurations may still be unreliable. To develop residential demographic multipliers for small geographies, we need to explore (1) the determination of an appropriate sample size threshold and (2) other means to increase sample sizes.

Minimum Sample Size

Burchell, Listokin, and Dolphin (2006) used 600 weighted observations—that is, the estimated number of households—as the minimum sample size in each housing configuration. Given that the average ratio of weighted to unweighted observations is about 21 to 1, they possibly assumed 30 unweighted observations, as in a *t*-test protocol.[12] CDA's analysis of the ratios between weighted and unweighted observations finds that this criterion may not be desirable. Because multiple weights are used, the ratio varies more when the number of unweighted observations decreases. Exhibit 8 shows that 600 weighted observations can be derived from only 13 unweighted observations.

[12] Because multiple sample weights are used, the ratio between weighted and unweighted observations varies by housing configuration and geography.

Exhibit 8

Relationship of Weighted and Unweighted Observations

Selected Configurations and Geography	PUMS Used	Ratio of Weighted to Unweighted		
		Minimum	Median	Maximum
Recently built unit sample				
Maryland, 45 configurations	Census 2000	17.6	21.2	24.8
	ACS 2010–2014	14.9	21.3	24.5
Mover sample				
Maryland, 45 configurations	Census 2000	17.8	20.8	22.8
	ACS 2010–2014	18.2	22.3	27.1
New Jersey, 75 configurations	ACS 2011–2015	17.8	22.7	26.8
Ohio, 73 configurations	ACS 2011–2015	17.6	22.3	28.4
Ohio, 93 PUMAs				
Three-bedroom single-family	ACS 2011–2015	13.6	21.0	31.6
Two-bedroom all multifamily	ACS 2011–2015	16.7	25.3	43.4
Two-bedroom townhome	ACS 2011–2015	8.2	21.5	37.0
Two-bedroom multifamily 5+ unit structure, rented	ACS 2011–2015	18.4	26.9	47.5

ACS = American Community Survey. PUMA = Public Use Microdata Area. PUMS = Public Use Microdata Sample.
Note: State-level ratios pertain to housing configurations of fewer than five bedrooms and various blended categories but exclude configurations that cannot generate multipliers.
Source: Community Data Analytics 2016 and 2017 Planning Ratio Estimation Program computations derived from 2000 census PUMS and from 2010–2014 and 2011–2015 ACS PUMS

Our recommendation of minimum sample size is 30 unweighted observations. In addition, estimates should be discarded by additional tests. One test is to identify if the value of an estimate decreases when the number of bedrooms increases. Based on the observation that the number of occupants positively correlates to the number of bedrooms, any multiplier that behaves differently should be considered as associated with an unacceptable sampling error. A second test is a coefficient of variation (CV) test. At the PUMA level, a stringent CV of 0.3 is generous for average household size but fails one-half of the school-age children estimates. One reason is that the value of one-bedroom and studio school-age children is close to 0, suggesting that the CV test should be applied only to two-bedroom or more configurations. The two tests are concurrent, but the CV test is more generous. When the number of unweighted observations is less than 30, the multipliers may pass a CV test at 0.4.

Other Means for Local Multipliers

Other means to increase sample size include (1) blending housing configurations, (2) avoiding age or grade differentiation, (3) expanding the geographical coverage, or (4) extending the time span of ACS PUMS records to more than 5 years.

Some types of housing are rarely built, such as owner-occupied multifamily units in rural areas, three- and four-bedroom rental multifamily units, and other five-or-more-bedroom units. Researchers can instead focus on popular configurations by combining all four-or-more-bedroom units into one category or not differentiating the tenure when the distribution is lopsided. Another possibility is to apply a known ratio between broad categories in terms of tenure or bedroom numbers in the same geography to derive a set of estimates for its subcategories. Applying these ratios assumes the ratios are uniformly distributed—an assumption that requires further study.

Differentiating multipliers by age cohorts or grade groups exacerbates the insufficient sample size problem. Even when the sample size seems adequate, the margin of error can be large. As such, such differentiation should not be conducted at the local level.

The other solution is to generate multipliers by a PUMA aggregate despite the fact that doing so weakens geographical specificity. Our preliminary study shows that an aggregate of five PUMAs provides reasonable estimates for most popular configurations. One way is to merge several contiguous PUMAs together. However, choosing PUMAs with unifying characteristics, such as whether a PUMA is rural or urban, seems to be more indicative.

Creating an extended ACS PUMS by pooling nonoverlapping records is another possibility. We can pool records from various ACS 1-year PUMS. This method involves using year-specific replicate weights. Combining nonoverlapping ACS multiyear PUMS requires scaling down replicate weights to prevent overestimation of weighted observations. If housing rent and value are involved, researchers have to develop dollar adjustment factors to inflate the monetary value to the end year. Pooling PUMS record could contain information originating more than a decade ago.[13] At the PUMA level, this method has to overcome the issue that the 2010 and 2000 PUMAs are not the same spatial units, even if the codes are the same.[14] Missouri Census Data Center provides a crosswalk to generate allocation factors between these the two sets of PUMAs. When the forward and backward allocation factors are nearly 100 percent, a prorated estimate works reasonably well. Otherwise, researchers face an uncertain degree of biases because of boundary changes.

More Research of Demographic Multipliers

The latest ACS PUMS records provide new possibilities for generating multipliers beyond the traditional school-age children and average household size. Notable examples are per-unit ratios of workers, commuters who use transit, numbers of cars available, persons who are foreign born, and so on. The use of additional variables can delineate samples by income groups or housing affordability and households living in condominiums or receiving welfare.

The need for multipliers for specialized housing—such as age-restricted development, transit-oriented development, and affordable housing—is increasing. The PUMS records, however, do not provide variables precise enough for these development types. If they are careful, researchers should be able to develop a surrogate sample based on multiple variables. The development of surrogate samples reminds us that if resources are available, post-occupancy surveys should be conducted to verify PUMS-based multipliers.

Another challenge is the possibility of multipliers for a spatial unit smaller than a PUMA or cutting across PUMAs, acknowledging that PUMA estimates are not uniformly distributed within. Can researchers use several variables to select ACS PUMS records from the region to develop a synthetic

[13] In the case of a pooled ACS 2005–2015 PUMS, the earliest year the householder moved into a unit is either 1996 or 2002 because of *MV* classification. The earliest year of structure built is 2000, because *YBL* groups together units built between 2000 and 2004.

[14] To conform to the requirement of a minimum of 100,000 persons, PUMA boundaries are modified after population count is available, usually 2 years after the decennial census.

geography that resembles the major attributes of the spatial unit in question? This process inevitably requires multiple iterations of adding and replacing records until optimal results are achieved (Simpson et al., 2017; Wong, 1992). The other option is to run a multivariate analysis to model multipliers by the determinants of housing configurations at the PUMA, county, and state levels to detect a pattern of concurring coefficients. Another path is to develop a simulation model for a quasi-experimental matching of larger geographies to smaller places (Rephann and Isserman, 1994). All these experimental models require resources that CDA has yet to acquire.

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