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Not all shrinking places are similar: The variegated nature of population decline in the United States

David N. Karp[a], Sharmistha Bagchi-Sen[b,*], Peter Rogerson[a]

[a] Department of Geography, University at Buffalo-State University of New York, Buffalo, NY, 14261, USA
[b] School of Geographical Sciences and Urban Planning, Arizona State University, Tempe, AZ, 85281, USA

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ABSTRACT

Shrinking cities have become almost ubiquitous during the long transition of post-industrial America. While many fear population losses to be a harbinger of economic decline, others have argued that the economic and demographic transition of a shrinking city need not be a death knell for those urban communities. In this study, we conduct an analysis of more than 10,000 U.S. census tracts experiencing population loss in order to better understand the variegated nature of population decline in the United States. Using high-dimensional cluster analysis, we classify tracts into seven distinct groups, and then assess group differences based on population characteristics and built environment indicators. Our findings show inter- and intraregional characteristics that are far from uniform. Our results imply that public policy responses cannot be developed as a one-size-fits-all strategy, nor should the outlook of urban shrinkage be understood as a nationally uniform crisis. Future work can build upon our typological definitions to offer additional insights valuable to local decision makers and leaders regarding the complex relationship between demographic change and associated socio-economic outcomes.

1. Introduction

Shrinking cities have become an American and international phenomenon over the course of the last several decades, posing a challenge for political leaders attempting to address the associated effects on the community and economy. In recent years, the topic has attracted much interest from academic scholars hoping to better understand the demographic, social, political, and economic drivers as well as to evaluate the outcomes, which are often negative. Historically, the causal processes associated with urban shrinkage are generally identified with three key areas: deindustrialization, suburbanization, and demographic change (Weaver, Bagchi-Sen, Knight, & Frazier, 2016). Shrinking cities in the United States epitomize a form of urban inequality, both across and within cities, and the impacts of loss are felt disproportionately within these places, which are generally poorer and less white/non-Hispanic than their growing counterparts (Bellman, Spielman, & Franklin, 2018; Franklin, 2021; Weaver, Bagchi-Sen, Knight, & Frazier, 2016). Further, the financially vulnerable position of local governments adds a compounding burden (Carbonaro, Leanza, McCann, & Medda, 2018), while they are still obligated to provide an array of public services from a diminishing fiscal budget. This scenario is ideal for exacerbating already existing inequalities within and between places and demographic groups.

While the story of shrinking cities may be most visible in places like Detroit, other areas across the mid-western Rust Belt, and the eastern-central Appalachian regions, the reality is actually much less uniform or clear cut. The data show that population loss is in fact extremely heterogenous and not limited to the Midwest or Appalachia. Also, population loss is not always a death knell of economic decline, but rather there are many places across the country and within metro areas that appear to be resisting economic decline despite the common expectation, or as silos even amongst broader regional despair. In this study, we aim to fill a gap in existing research on variability within the contemporary examination of shrinking cities, specifically with regard to comparative conditions of places experiencing recent population loss. A more complete and nuanced understanding of where shrinking places are geographically located, and their compositional characteristics, can contribute to future research relating to broader questions of urban transformation and transition, political and economic restructuring, and targeted policy strategies aimed at facilitating urban revitalization and addressing issues of socio-economic inequality.

In this research, our goals are to address the internal heterogeneity of

* Corresponding author.
E-mail address: Sharmistha.Bagchi-Sen@asu.edu (S. Bagchi-Sen).

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places experiencing population loss and to provide a taxonomy to understand the complexity surrounding population decline. This is done through an analysis of relevant variables that describe demographic, socio-economic, and built environment profiles. Multiple clusters are detected and uniquely assigned to census tracts. The geographic distribution of all census tracts within each taxa is assessed to explain inter-metro patterns across the country. At the regional, or intra-metro scale, we look at Core-based Statistical Areas (CBSAs),[1] to identify the dominant cluster within each CBSA, and calculate relative entropy to consider the degree of cluster variety within each metro area.

2. Background

Shrinking cities have occupied the attention of researchers in many different contexts, including their relation to the global urban system, intraregional economic fortunes, and urban policy. The literature on shrinking cities is replete with examples. These examples highlight the fact that this is a phenomenon that is occurring globally, and it is one where much thought has already gone into questions of planning, policy, and management. We review these contexts below.

An important early collection of studies of shrinking cities is the edited book of Pallagst et al. (2009). Here the authors describe the problems of shrinking cities in an international context, and they discuss approaches to revitalizing shrinking cities, as well as planning and policy making for shrinking places. Hartt (2021) discusses shrinking cities primarily from a Canadian perspective, but he sets his study within a broader global context. In particular, he reviews the many various attempts at rightsizing and smart decline, giving examples from places that dominate the literature on the subject, including Youngstown, OH (Rhodes, 2019; Rhodes & Russo, 2013), Detroit, MI (Krohe, 2011; Reese, Sands, & Skidmore, 2014), Buffalo, NY (Schilling, 2009), and Leipzig, Germany (Bontje, 2005; Couch, Karecha, Nuissl, & Rink, 2007; Rall & Haase, 2011). Schilling and Logan (2008) also discuss rightsizing, focusing on green infrastructure in the U.S. Rust Belt cities. Rieniets (2009) gives a history of shrinking cities in a global context, and focuses upon demographic factors now acting to exacerbate trends toward shrinkage. He discusses planning challenges and paradigms aimed at the management of decentralization.

The emergence of global cities continues to realign economic and political power at multiple scales (Pallagst, Aber, Audirac, Cunningham-Sabot, Fol, & Martinez-Fernandez, 2009; Sassen, 1991). From this, the resultant interregional competition has come to drive contemporary urban governance and policy decisions that highlight growth and the importance of agglomeration economies. Such global, national, and regional competition among places continue to lead to the emergence of peripheral cities, and thereby populations that are peripheral to the working of the national and global economies. At the local level, the *dual city*, whereby pockets, or enclaves of development have been carved out within a broader shrinking/declining region, manifests the unequal outcomes of current economic development policies. These enclaves are most often touted as solutions to reverse the tide; however, these enclaves of investment and prosperity perpetuate uneven development given the limitation of spillover effects (Silverman, 2020). Many ideas have been suggested for more active planning efforts in declining cities. Nefs, Alves, Zasada, and Haase (2013) note that such places may have potential in serving as green retirement places, attractive to retirees. They outline ways in which particular challenges (e.g., providing recreational opportunities, repurposing vacant space, etc.) might be initially addressed. Hollander and Németh (2011) argue for smart decline, where principles of social justice and equity are given full consideration as decline is managed. Cortese, Haase, Grossman & Ticha (2014) discuss policies aimed at maintaining social cohesion in the face of decline, focusing on Ostrava, Genoa, and Leipzig, and arguing that such policies have received only little attention.

While shrinking cities show correlation of population loss with economic decline, scholars argue that the pattern is not the same everywhere (Hirt & Beauregard, 2019), and in fact the data show that prosperous cities and neighborhoods do exist, despite shrinkage (Hartt, 2019; Ribant & Chen, 2020). Weaver, Bagchi-Sen, Knight, & Frazier (2016) explore both shrinkage and decline as independent *and* coterminous phenomena, demonstrating two important points: (1) decline is not limited to places losing population, or shrinking cities, showing that shrinkage is not a prerequisite for decline, and (2) while decline does occur in both growing *and* shrinking places, it is found to have an interaction effect, increasing the pace and severity of shrinkage when observed simultaneously with population loss. They are able to empirically demonstrate a positive interaction effect between shrinkage and decline by analyzing indicators of physical forms of distress, such as housing vacancy, abandonment, age of structure, and other variables evaluating quality of housing inventory.

Related research considers a variety of topics to better understand the nature and dynamics of shrinking cities, including evaluating sub-regional geographies of shrinkage and uneven patterns of decline (Silverman, 2020; Silverman, Yin, & Patterson, 2013), understanding changes to the built environment and variability in neighborhood quality (Hollander, Johnson, Drew, & Tu, 2019, Hirt & Beauregard, 2019; Hollander, Hartt, Wiley, & Vavra, 2018), and assessing policy responses and shifting perceptions of governing shrinking places (Akers, 2013; Hartt, 2020). Within the framework of challenging pro-growth dogma, Mallach (2015) notes the principal importance of geography and scale, specifically, that the criteria for how *success* is defined, measured, and benchmarked are critically relevant when studying policy responses to shrinkage.

The idea that shrinking cities are not as expendable as they are purported to be suggests that these places serve a vital purpose for resource extraction (e.g., debt service, cheap labor) or policy experimentation (Akers, 2013) for the global core, as well as maintaining sub-regional enclaves where growth, wealth, and reinvestment are not still present (or returning). Silverman (2020) describes this as the *dual city*, where a central core may be moving in an opposite direction from the majority of the city's neighborhoods. This line of inquiry, focusing on disparities within regions, is what Mallach (2015) explores in studying Rust Belt cities, where revitalization is almost exclusively restricted to downtown/core areas. He tracks the discrepancy between job growth in the city and loss of resident jobholders working in the city, explaining that the revival of economic activity is largely benefiting workers commuting from outside of the city, and that jobs being added are held by a more educated workforce, suggesting that the transition from manufacturing to service-based industry appears to correspond to a shedding of the blue-collar jobs that once supported middle-class families. In what he terms an "uncoupling" of the economic and demographic city, the uneven geography of urban redevelopment and *success* in the city is primarily defined by the economic prosperity of private business and a few core neighborhoods, while the demographic base residing in the city's residential areas is left behind and neglected.

Identifying and learning from shrinking cities that are not economically stressed is interesting for policy makers, as urban planners and local leaders strive to find workable solutions for their struggling cities. Hartt (2019) approaches the fact that shrinking cities are not homogeneous, and identifies places that are economically prospering, despite experiencing population loss. His analysis considers the conditions under which shrinking cities are doing well economically, noting that 27% were wealthier than their neighbors and had a greater ability to attract talent (location quotient was greater than 1.0 in 97% of

[1] Core-based Statistical Areas, or CBSAs, are geographic regions, comprised of multiple adjoining counties, defined based on economic commuting patterns. These regions are non-political jurisdictions that are established for the purpose of data collection and publication. They are named for the core, or major city or county at the center, and describe what is colloquially understood as the "metro area".

prosperous shrinking cities v. 78% of all shrinking cities). He also found that severity and persistence of population loss showed no relationship with income.

In line with assessing patterns of heterogeneity amongst shrinking cities, Ribant and Chen (2020) conduct an analysis of shrinking metropolitan and micropolitan areas in the United States to classify cities into seven distinct typologies. Different from the analysis we develop in our study here, Ribant & Chen conducted their analysis at the level of city and metropolitan area, and restricted their definition of shrinkage to places that both lost population *and* were designated in economic decline. Cities were assigned to groups based on size and local context relative to metro/micropolitan core – classifications differentiated shrinking central city, inner/outer suburb of shrinking/growing core city, and cities within small metro or micropolitan area. Their analysis compared the geographic distribution of their seven classes, and assessed differences in demographics between groups. Additionally, they conducted a cluster analysis on one of these groups (81 large central cities, primarily located in the Rust Belt of the Northeast/Midwest). The analysis segmented the data into 2 groups, which are principally differentiated by their share of foreign-born residents, which they classify as "culturally transforming", with the majority located along the Northeast corridor (between Washington DC and Boston). Through their analysis of broader geographic patterns of all shrinking cities, they find that suburbs are more commonly found to be shrinking in metros with a shrinking core, and that only seven metro areas accounted for more than 25% of all shrinking cities.

There is a wealth of other literature, mostly on growing cities, but also shrinking cities, examining geographic patterns and spatial dynamics. Reis, Silva, and Pinho (2016) provide a fairly comprehensive review of different spatial metrics used throughout the literature to analyze and provide indicators of urban growth and shrinkage. These features include growth metrics describing expansion, sprawl, polycentrism and increasing density; as well as shrinkage indicators including distribution of vacant land and housing, decaying buildings, land-use fragmentation, demolitions, and proliferation of open space. While these indicators are valuable for understanding changing urban form and the dynamics of the built environment within growing or shrinking places, in our analysis we aim to add a spatial analysis of shrinkage across a broader scope (distribution across the United States) and at a finer scale (classification of census tracts).

The above literature shows that patterns and dynamics of population loss and associated characteristics for a country as vast and diverse as the United States need to be examined on a continual basis to identify the broader context within which local patterns are emerging. Such an understanding informs theory development (e.g., what may cause urban inequalities, who is empowered, who needs to be empowered) and policy (e.g., what sort of empowerment and for whom).

3. Data and methods

In this study, census tracts are used for cluster analysis based on a set of indicators across three key characteristics: demographic, economic, and housing (Fig. A1 in the Appendix). Both inter- and intraregional patterns are examined: distribution across U.S. census divisions and within CBSAs (core-based statistical areas). Data on census tracts[2] are obtained from the 2009, 2017, and 2018 American Community Survey (5-year estimates). Population change is calculated between 2009 and 2017. Urban-rural continuum codes are used from 2013 data prepared by the USDA's Economic Research Service (Economic Research Service & United States Department of Agriculture, 2013). Census tracts are cross-walked to CBSAs based on county FIPS codes,[3] using data from the National Bureau of Economic Research (National Bureau of Economic Research, 2020). All variables are from 2017 estimates from IPUMS[4] except that variables for "Field of Bachelor's Degree" are used from 2018 data, and downloaded from the Social Explorer.[5] All data processing, analysis, and visualization are undertaken using R (R Core Team, 2021). Maps are produced in QGIS (QGIS Development Team, 2020).

We began with 52,444 census tracts, of which 22,314 experienced population loss during the study period. The following tracts are excluded: (a) tracts that record a residential population of zero in either study year ($n = 23$); (b) tracts that are located outside of the 50 states or Washington DC ($n = 597$); (c) tracts that recorded population loss at a below median rate, where the national median rate of loss is calculated as 7.1% loss for the time period ($n = 10{,}868$), and (d) tracts that are missing data across any of the variables ($n = 442$). This subset of tracts is used to undertake a principal component analysis ($n = 10{,}384$)[6] of 138 variables[7] (see Table A1 in the Appendix); 45% of the variation in the data is explained with the first five principal components (PCs). Each of the first five PCs have eigenvalues greater than one, indicating that they provide at least as much explanatory value as a single variable. We also observe that the first principal component (PC1) explains 20.9% of the variance, PC2 explains an additional 10.2%, and PC3, PC4, and PC5 respectively add an additional 6.6%, 3.9%, and 3.5%. After PC5, each additional PC offers less than 3% additional explanation of the variability in the data. We used the variable loadings to rank order variables based on importance for each of the associated five principal components selected. The top three variables for PC1-PC5 are included in the Appendix (Table A2). These variables include indicators related to education and type of college degree (PC1), Hispanic ethnicity and languages spoken at home (PC2), race, education of minority races, and adults living alone (PC3), education by race and age, and young adults living with their parents (PC4), and education by age, sex, and degree type (PC5). We use the rotated factor scores associated with these first five components as inputs for a *k*-medoids clustering procedure (described in the Appendix). From the clustering analysis, a unique group identifier is assigned to each of the 10,384 census tracts. Given that census tracts provide a high-resolution scale of analysis, a homogenous "neighborhood" may be subdivided into multiple census tracts. Tracts are also aggregated to the level of CBSA and Census Division in

[2] The universe of Census Tracts was selected for all US states (including Washington, DC), using the 2010 vintage of geographic boundary file.

[3] Federal Information Processing Standards (FIPS) codes are identifiers developed and maintained by the U.S. government standardize data collection and processing across government and non-government agencies. The U.S. Census Bureau publishes its tabulated data with numeric codes that provide unique identifiers for specific geographic areas (such as states, counties, and census tract boundaries).

[4] Data are downloadable from IPUMS NHGIS (Manson, Schroeder, Van Riper, & Ruggles, 2019).

[5] Data are downloadable from SocialExplorer.com (U.S. Census Bureau, 2020).

[6] Of the 10,384 tracts used in this part of the analysis, (a) 855 have no CBSA code listed, so these are assumed not part of a CBSA; (b) 2034 do have a CBSA code, but are located in a county that the USDA ERS defines as "Counties in metro areas of fewer than 250,000 population" ($n = 1027$), or "Nonmetro counties" ($n = 1007$); (c) these 2 groups (a & b above) ($n = 2889$) are excluded from the comparison of medians and from the mapping. The 1007 "non-metro" tracts do have a CBSA code listed, and therefore are not excluded with the initial set of 855 (group a above). It is possible these may be legacy codes.

[7] The complete list of variables is included in Appendix A (Table A1).

order to conduct analyses of cluster distribution at regional scales. A final subset of tracts is then selected by using tracts in metro areas, where CBSAs had a population of at least 250,000 ($n = 7495$) ,[8] to examine cluster characteristics.

In the analysis, demographic variables include median age, percent White non-Hispanic, African American, Asian, and Hispanic, and percent foreign born. Household variables included percent of households that were female-headed, English-only speaking, and Spanish speaking. Educational attainment includes percent of adults with High School diploma, Bachelor's degree, or Graduate degree. Economic variables include median household income (in U.S. dollars), poverty rate, and Gini coefficient. Employment related variables include unemployment rate and percent of jobs in each of the following industry sectors: Arts and Entertainment; Business and Finance; Computer Science and Engineering; Finance, Insurance, and Real Estate; Food, Maintenance, Personal Care; Healthcare industry (NAICS AH33E023, AH33E050); Healthcare occupation (NAICS AH3SE020, AH3SE056); Industrial and Manufacturing; Information Services; Production and Transportation; and Retail. Variables related to housing include vacancy rate, percent of housing units that were renter occupied, and median housing value (in U.S. dollars). These variables are included as indicators of area conditions at a single point in time, that is, the end of the study period during which population loss was evaluated. Our decision not to look at change over time for these explanatory variables is intentional; we are interested in the current characteristics of places that already lost population in order to understand variation among those places, rather than to identify any specific causal associations, for which we would be interested in values from the start, as well as change during the study period.

Interregional patterns: To evaluate the distribution of tracts by cluster across the United States, we calculate the proportion of all tracts in each cluster that are located in each of the nine census divisions (New England, Mid-Atlantic, South Atlantic, East North Central, East South Central, West North Central, West South Central, Mountain, Pacific) (see https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf). We also map the primary cluster observed in each CBSA to convey the spatial pattern of cluster types.

Intraregional patterns: To evaluate the degree to which CBSAs exhibit a variety of clusters, we calculate a relative entropy value at the level of the CBSA. Relative entropy is high when a CBSA has a variety of types of clusters, and is low when the CBSA features one predominant cluster type, with few tracts in any of the other clusters. This calculation involves aggregating census tracts to the CBSA where they are located, and then computing the proportion of all shrinking tracts within the CBSA classified in each cluster as $x_i = n_i/N$, where n_i is the number of cluster i tracts, and N is the total number of shrinking tracts in the CBSA. Entropy, E, is then calculated for each CBSA as $\mathrm{E} = -\Sigma_{i=1}^{k} x_i ln(x_i)$, where the sum is over the k number of clusters. We then standardize these values by calculating Relative Entropy, as $R = (E/ln(k))*100$, where k is the total number of clusters. Index values for R range from zero, where there is complete concentration of a single cluster class, to 100, where the mix of cluster classes is completely even. To visualize the results, the CBSA-level relative entropy values are mapped.

4. Results

The number of tracts in each cluster classification ranges from 641 (6.2%) to 2625 (25.3%) (Table 1). Table 1 shows that the majority of these shrinking tracts are located in large metropolitan areas (72.2%) –this is consistent with the tract distribution pattern in the US as a whole, where 75.8% of tracts are located in large metro areas. However, there is significant variation between individual clusters, with percentages ranging from 33.8% (cluster 1: working-class homeowners) to 96.7% (cluster 5: highly-educated, immigrants in high-skilled jobs, homeowners). Cluster 1 is the main outlier with the other six clusters having at least two-thirds of tracts in metro areas.

Table 1
Distribution by cluster classification and proportion in large metro areas

Clusters	Distribution of census tracts by cluster		Proportion of tracts per cluster in large metro area	
	n	%	*n*	%
Cluster 1	2625	25.3%	887	33.8%
Cluster 2	1621	15.6%	1172	72.3%
Cluster 3	1452	14.0%	1206	83.1%
Cluster 4	1904	18.3%	1613	84.7%
Cluster 5	641	6.2%	620	96.7%
Cluster 6	1074	10.3%	1010	94.0%
Cluster 7	1067	10.3%	987	92.5%
All tracts	10384	100.0%	7495	72.2%

Note: Cluster classification is based on a k-medoid algorithm, where $k = 7$. Percentages are calculated column-wise where the denominator is total shrinking tracts ($n = 10{,}384$). "Large metro areas" is an assigned designation of Rural-Urban Continuum Codes (RUCC)'s 1 and 2, where the population for the entire metropolitan area is greater than 250,000 people. The percentages are calculated row-wise, where the denominator is the total tracts in each cluster (e.g., Cluster 1: 887/2625 or 33.8%).

Next, the characteristics of each of the seven clusters are examined with a selection of relevant variables. Table 2 shows the median values of each variable for each cluster (medians are calculated based on all tracts within that cluster). The dataset for this part of the analysis is limited to tracts in large metro areas only ($n = 7495$). The table is coded by color scale according to value distributions for each row (variable) across the seven clusters (columns): minimum (darker blue), median (white), and maximum (darker red). Cluster labels are assigned based on distinguishing characteristics: Cluster 1 - working-class homeowners; Cluster 2 - low socioeconomic status renters and homeowners; Cluster 3 - service sector workers in vacant/undervalued neighborhoods; Cluster 4 - highly-educated, middle-class, homeowners; Cluster 5 - highly-educated, immigrants in high-skilled jobs, homeowners; Cluster 6 - high-earning, homeowners in business and tech jobs, in high-priced markets; Cluster 7 - immigrants, renters in low-skill service sector.

4.1. *Cluster 1: working-class; homeowners*

The *demographic* profile shows that the median age of residents (43.7) is older than other clusters. In addition, there are high proportions of white, non-Hispanic residents (90%); high rates of English-only speaking households (96%); high rates of residents with a high school diploma as their highest educational achievement (39%); above average rates of female-headed households (13%); and a low proportion of foreign born (19%).

Economic indicators show the average median income as $48.9k, which is about average relative to all clusters. The percent living below the poverty line is low (13%) and the measured Gini coefficient is low (0.04). There are high rates of jobs in production and transportation (30.1%), manufacturing (14.6%), and retail (12%), but low rates in information (1.1%) and arts and entertainment (0.8%). *Housing* indicators show relatively high rates of vacancy (12%), low rates of renter occupied units (24%), and a low median housing value ($115,200).

4.2. *Cluster 2: low socioeconomic status; renters; and homeowners*

The *demographic* profile shows that the median age of residents (35.5) is younger than other clusters. There are low proportions of white, non-Hispanic residents (49%) and Asian (1.0%) and high

[8] This designation is based on our own grouping of the Urban Rural Continuum Codes (RUCC) that the USDA ERS produced for 2013. In our definition "large urban metro areas" included tracts in counties with a RUCC designation of 1 (Counties in metro areas of 1 million population or more) or 2 (Counties in metro areas of 250,000 to 1 million population).

Table 2
Cluster characteristics.

		Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7
Demographic	Median Age (yrs)	43.7	35.5	36.4	42	35.35	45.85	33.1
	White Non-Hispanic (%)	90.0	49.0	4.0	78.0	62.0	82.0	11.0
	Black (%)	2.0	25.0	88.0	4.0	6.0	2.0	4.0
	Asian (%)	0.0	1.0	0.0	2.0	6.0	4.0	2.0
	Hispanic (%)	3.0	10.0	2.0	7.0	10.0	6.0	70.0
	Female HH (%)	13.0	13.0	16.0	12.0	10.0	12.0	11.0
	Foreign born (%)	19.0	36.0	14.0	44.0	56.0	51.0	67.0
	English-only speaking HH (%)	96.0	87.0	95.0	87.0	77.0	85.0	31.0
	Spanish speaking HH (%)	2.0	7.0	3.0	5.0	7.0	4.0	57.0
	HS Diploma (%)	39.0	34.0	36.0	27.0	15.0	14.0	28.0
	Bachelors degree (%)	11.0	11.0	7.0	20.0	31.0	32.0	8.0
	Graduate degree (%)	5.0	5.0	3.0	11.0	21.0	25.0	3.0
Economic	Gini Coefficient	0.04	0.05	0.06	0.04	0.05	0.04	0.05
	Median HH Income ($)	48,929	36,368	25,882	65,208	60,410	101,133	38,750
	Poverty (%)	13.0	25.0	36.0	8.0	14.0	5.0	25.0
	Unemployment (%)	6.0	10.0	17.0	5.0	5.0	4.0	8.0
	Business&Finance (%)	2.8	2.8	2	5	7	7.8	1.8
	CompSci&Engineering (%)	2.5	2.4	1	4.4	6.1	5.9	1.3
	Art&Entertainment (%)	0.8	1.1	0	1.7	5.1	2.8	0.8
	Healthcare (by occupation) (%)	2.3	3.1	5.5	2	1.1	0.9	2.5
	Food/Maint./Pers. Care (%)	12.9	17.7	20.4	11.7	11.45	7.7	20.4
	Production&Transportation (%)	30.1	25.15	23.6	18.1	9.35	8.9	31.7
	Industrial&Manufacturing (%)	14.6	9.8	8.1	8.2	4.9	7	9.1
	Fin/Insur/Real Estate (%)	4.5	4.3	3.9	7	7.6	10	3.8
	Retail (%)	12	12.5	10.9	11.4	8.3	8.5	11.3
	Healthcare (by industry) (%)	13.5	14.6	20.45	14.6	12	13.55	11
	Information Services (%)	1.1	1.4	0.8	1.9	3.8	2.5	1.1
Housing	Vacancy (%)	12.0	15.0	24.0	8.0	11.0	7.0	10.0
	Renter Occupied Units (%)	24.0	52.0	56.0	27.0	63.0	17.0	56.0
	Median Housing Value ($)	115,200	99,400	65,000	204,400	376,600	416,950	170,350

Color Key:	MIN			MEDIAN			MAX

percentages of African American (25%) and Hispanic (10%); high rates of female-headed households (13%); and mid-range rates of English-only speaking households (87%) and Spanish speaking households (7%). There are high rates of residents with a high school diploma as their highest educational achievement (34%) and a low population of foreign born (36%).

Economic indicators show a low average median income of $36.4k. The percent living below the poverty line is high (25%) and unemployment is high (10%). In terms of job sectors, there are high rates of jobs in healthcare (3.1%), food, maintenance and personal care (17.7%), production and transportation (25.2%) and retail (12.5%), but low rates in finance, insurance, and real estate (4.3%) and computer science and engineering (2.4%). *Housing* indictors show high rates of vacancy (15%), mid-range rates of renter occupied units (52%), and a low median housing value ($99,400).

4.3. Cluster 3: service sector workers; vacant/undervalued neighborhoods

The *demographic* profile shows very high rates of African Americans (88%) residents and low Hispanic population proportions (2%). The proportion of female-headed households is high (16%), English-only speaking households is high (95%) and population with bachelor's degrees (7%) and graduate degrees (3%) is both low.

Economic indicators include high poverty (36%), low median income ($25.9k), and a high Gini coefficient (0.06). Unemployment is also high (17%) and the percentage of foreign born is low (14%). Job sector indicators show low rates of jobs in business and finance (2%), computer science and engineering (1%), information services (0.8%), and arts and entertainment (0%). Job rates are high in healthcare (20.5%) and food service, maintenance, and personal care (20.4%). *Housing* indicators include high vacancy (24%) and renter occupied units (56%), and low median housing value ($65,000).

4.4. Cluster 4: highly-educated; middle-class; homeowners

Demographics show slightly high median age (42), a high percent White and non-Hispanic (78%), and high rates of bachelor's (20%) and graduate (11%) degrees. There are mid-range rates of foreign-born population (44%).

Economic indicators include high median household income ($65k), low poverty rates (8%), low Gini coefficient (0.04) and low unemployment (5%). The employment profile shows high rates of business and finance (5%), computer science and engineering (4.4%), finance, insurance, and real estate (7%), healthcare (14.6%). *Housing* indicators show low vacancy rates (8%) and low rates of renter occupied units (27%). Median housing value is high ($204,400).

4.5. Cluster 5: highly-educated; immigrants in high-skilled jobs; homeowners

Demographics show low median age (35.4), high proportion of Asian (6%) and Hispanic (10%) residents. Female-headed households (10%) and English-only speaking households (77%) are relatively underrepresented, bachelor's (31%) and graduate (21%) degrees are overrepresented, and the percentage with high school diploma as highest educational achievement is low (15%). Foreign-born population is high (56%) in this cluster.

Economic indicators include a mid-range median household income ($60.4k), poverty rate (14%), and Gini coefficient (0.05). Unemployment is low (5%). Employment patterns show high rates of business and finance (7%), computer science and engineering (6.1%), arts and entertainment (5.1%), and information services (3.8%). Rates are low for production and transportation (9.4%), retail (8.3%), and industrial and manufacturing (4.9%). *Housing* indicators show high rates of renter-occupied units (63%) but median housing values are high ($376,600).

4.6. Cluster 6: high-earners; homeowners; high-priced housing markets

The *demographic* profile shows high median age (45.9), and high rates of White, non-Hispanic (82%) and Asian (4%). Hispanic (6%) and Spanish-speaking households (4%) percentages are low, and the attainment of bachelor's (32%) and graduate (25%) degrees is higher than average.

Economic indicators show a very high median household income ($101.1k), low poverty (5%), unemployment (4%), and Gini coefficient (0.04). Job sector profiles show high rates of jobs in business and finance (7.8%), computer science and engineering (5.9%), and finance, insurance, and real estate (10%). Rates are low in food services, maintenance, and personal care (7.7%), production and transportation (8.9%), and retail (7%). *Housing* indicators show low vacancies (7%) and renter-occupied units (17%). Median housing value is the highest of any cluster ($416,950).

4.7. Cluster 7: immigrants; low-skill service workers; renters

Demographic indicators show a relatively young median age (33.1), a high proportion of Hispanic residents (70%), a high rate of Spanish-speaking households (57%), and a very high rate of foreign-born (67%). College (8%) and graduate (3%) degree attainment rates are very low.

Economic indicators show a low median household income ($38.8k), a high rate of poverty (25%), and high unemployment (8%). *Job sector* profiles show high rates of jobs in food service, maintenance, and personal care (20.4%) and production and transportation (31.7%). Rates are low for business and finance (1.8%), finance, insurance, and real estate (3.8%), and healthcare (11%). *Housing* indicators show low vacancy (10%), and high renter-occupied units (56%). Median housing value is mid-range ($170,350).

Fig. 1 shows the distribution of each cluster across the nine U.S. census divisions. Most clusters have at most a plurality of tracts in one region, where a cluster accounts for 20–30% of total tracts. Clusters 2 (low socioeconomic status; renters; and homeowners), 3 (service sector workers; vacant/undervalued neighborhoods), and 7 (immigrants; low-skill service workers; renters) fit the perception of shrinking places, while the other four show low or average vacancy rates, poverty and unemployment rates, and average or high rates of educational attainment.

The geographic distribution can be used to also label clusters 1, 2, and 3 as Midwest/Rustbelt, clusters 4 and 5 (highly educated; middle class; homeowners, and highly-educated; immigrants in high-skilled jobs; homeowners, respectively) as Eastern Seaboard, cluster 6 (high earners; homeowners; high-priced housing markets) as Bi-Coastal, and cluster 7 (immigrants; low-skill service workers; renters) as West Coast/Mountain/Sunbelt. All clusters are represented in every region; however, some are significantly underrepresented – cluster 3 (service sector workers; vacant/undervalued neighborhoods) has minimal representation in New England and Pacific; cluster 7 (immigrants, low-skilled service workers, renters) has minimal representation in New England and East South Central. Other clusters have a small fraction in New England and Mountain (Clusters 1 and 2 – mostly working class and/or low socio-economic status), in West North Central (Clusters 3 and 7 – mostly service workers, undervalued neighborhoods, renters), and in East South Central (Clusters 4, 5, and 6 – highly educated, high earners, homeowners, high priced housing markets).

Fig. 2 shows the distribution across metropolitan areas. The dominant cluster (based on a plurality of tracts) for each of the 182 large metro CBSAs is coded on the map. Clusters 1 (working class; homeowners), 2 (low socioeconomic status; renters; and homeowners), and 4 (highly-educated, middle-class, homeowners) are each dominant in at least 40 CBSAs (more than 20% of the total); the other four clusters are each dominant in less than 10% of CBSAs, with cluster 5 (highly-educated, immigrants in high-skilled jobs, homeowners) dominant in the fewest number of CBSAs ($n = 4$). Clusters 1 (working class but mostly homeowners), 2 (low socio-economic status with a mix of renters and homeowners) and 3 (service sector workers in vacant/undervalued neighborhoods) are present across the Midwest, Appalachian, and Southern CBSAs but cluster 2 also stretches across the lower plains and mountain states.

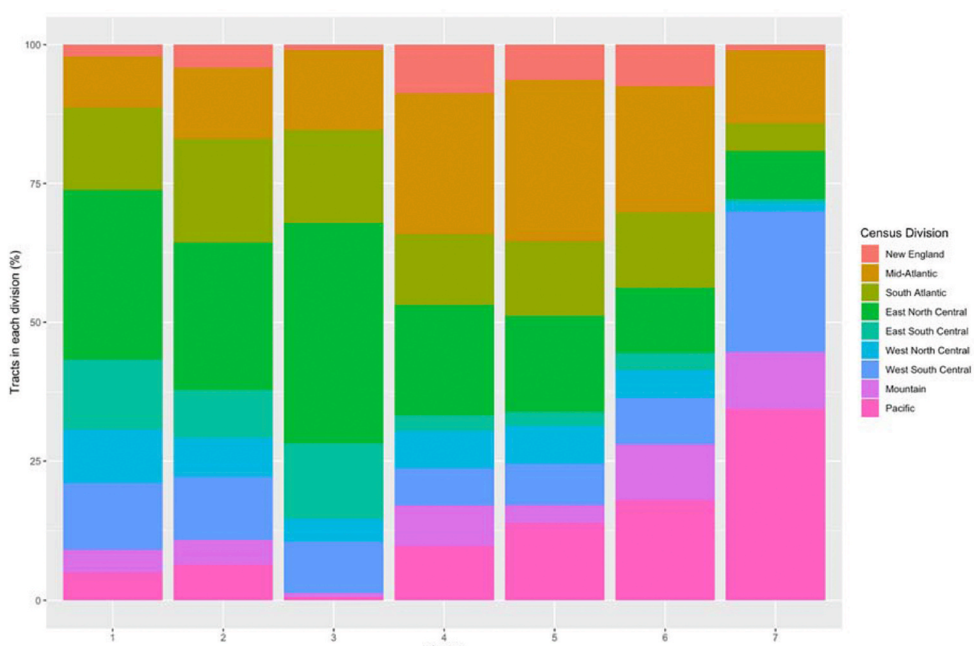

Fig. 1. Interregional distribution of clusters
Note: The figure displays regional distributions of census tracts for each of the seven clusters, across the U.S.Census Bureau' defined nine census divisions. Each bar in the chart includes 100% of the shrinking tracts percluster, with the color coding associated with each census division.

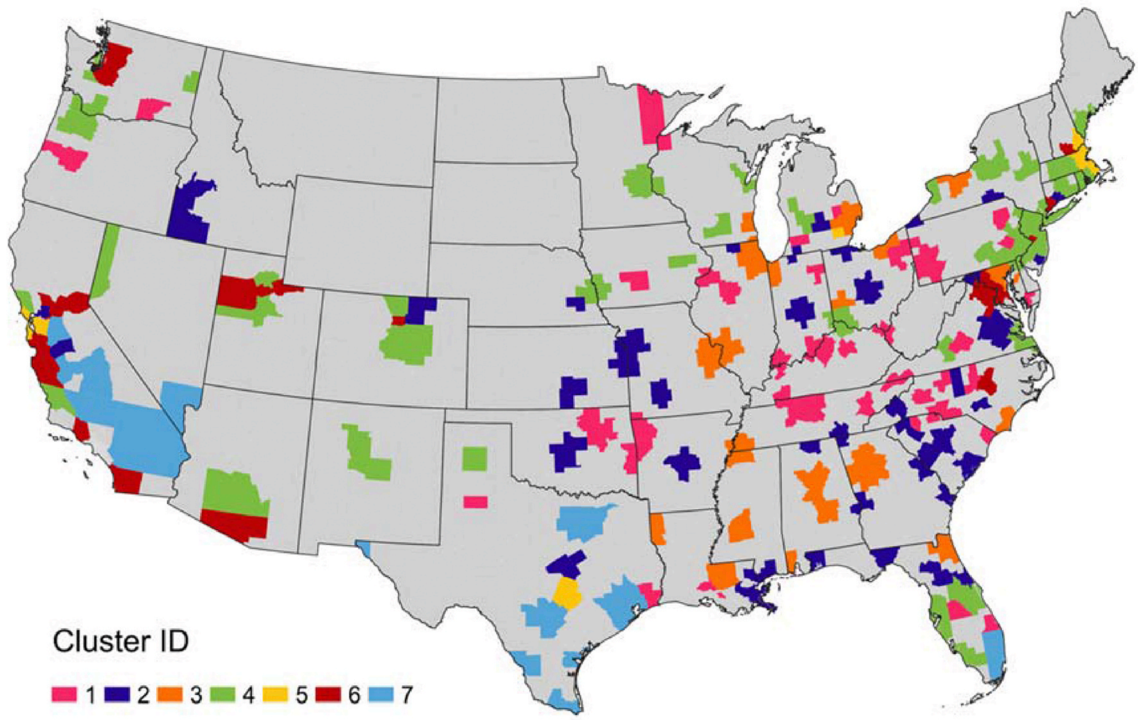

Fig. 2. Intermetropolitan distribution of (dominant) clusters
Note: Core-based Statistical Areas (CBSAs) are mapped in the figure, displaying the dominant cluster, or the cluster for which the majority of census tracts are assigned within the metro area. Cluster IDs are indicated by unique color and correspond to cluster labels are described as follows. Cluster 1: working class; homeowners; Cluster 2: low socioeconomic status; renters; and homeowners; Cluster 3: service sector workers; vacant/undervalued neighborhoods; Cluster 4: highly educated; middle class; homeowners; Cluster 5: highly-educated; immigrants in high-skilled jobs; homeowners; Cluster 6: high earners; homeowners; high-priced housing markets; Cluster 7: immigrants; low-skill service sector; renters.

Cluster 4 (highly educated; middle class; homeowners) appears dominant in several Northeast, upper Midwest, Southwestern, and Pacific CBSAs. There are also multiple CBSAs in Florida where cluster 4 appears. Cluster 5 (highly educated; immigrants; high skilled jobs; homewoners) appears in Northern California (Bay Area), East Texas (Austin), Massachusetts (Boston), and Southern Michigan (Ann Arbor). Cluster 6 (high-earning; homeowners in business and tech jobs; in high-priced markets) is most dominant in the Southwest and Pacific states, with one East Coast exception (DC/Northern Virginia). Cluster 7 (immigrants; low-skill service sector, renters) appears in Southern California (Central Valley and Inland Empire) and Nevada (Las Vegas), East and Southeast Texas (Dallas, Houston, San Antonio, and along the Mexican border), and Southern Florida (Miami).

Next, the relative entropy values for each CBSA are mapped showing the degree of concentration of a single cluster type (low entropy = red) versus diversity of multiple cluster types (high entropy = blue). The relative entropy index values range from zero to 97.5, with a median of 64.3. Entropy values do appear to be positively correlated with the number of shrinking census tracts, and the size of the metro population—this reflects the fact that larger metros tend to have more diverse populations, land uses, and commercial activity. Additionally, smaller CBSAs, with fewer tracts inherently have less opportunity for a diverse representation of clusters to be present. Fig. 3 shows that the patterns show high levels of diversity along the Northeast Corridor (Boston to Washington D.C.), and across the Rust Belt/Plains (Pittsburgh to Kansas City). CBSAs within southern states (South Carolina, Florida, Arkansas, Texas), Mountain states (Denver, Salt Lake City) and California show lower entropy values (less diverse within a CBSA). However, there is also a greater mix of entropy values across those states/regions, meaning there is a wider range of internal composition when comparing neighboring CBSAs. These areas indicate higher levels of concentration of a single type of cluster, or more homogeneous CBSAs.

As Fig. 3 demonstrates, there is much interregional variation in terms of *intra*-CBSA level diversity. The variety and spatial arrangement of clusters is shown in Fig. 4—here, we take a closer look at selected CBSAs to demonstrate the distribution of cluster types across each metro region. The selection of CBSA-level maps shown in Fig. 4 highlight four key characteristics: high level of diversity, based on relative entropy scores (panel A); high rate of CBSA-level shrinkage (panel B); spatially distributed tract-level shrinkage (panel C); and spatially concentrated tract-level shrinkage (panel D). In each panel (column of map layouts) the top three CBSAs are displayed.

In panel A, the maps are multi-colored, based on the high entropy scores, which indicate a variety of cluster classes. The three selected CBSAs are Kansas City, MO (97.5), Atlanta, GA (93.0), Orlando, FL (92.2), representing the South Atlantic and West North Central census divisions.

The CBSAs with the highest rates of shrinkage are all in the East North Central census region (panel B): Toledo, OH (5.2%), Flint, MI (5.1%), and Youngstown, OH (3.7%) (split with Middle Atlantic census division), and Detroit, MI (3.6%). Toledo, OH, Flint, MI and Youngstown, OH appear less diverse compared with Detroit, MI or any of the CBSAs in panel A. Additionally, Toledo, Flint, and Youngstown show a higher representation of cluster 1 (working class; homeowners), which consists of larger peripheral, suburban tracts (which generally means less densely populated). Detroit also includes some cluster 1 tracts (not captured at the scale of the map in the figure); however the downtown core includes a large block of cluster 3 tracts (service sector workers in vacant/undervalued neighborhoods). Such inner-city enclaves also show up in Flint and Toledo, although they are less widespread. Cluster 2 (low socioeconomic status; renters; and homeowners) and cluster 4 (highly educated; middle class; homeowners) also appear to co-locate on the periphery of cluster 3 (service sector workers; vacant/undervalued neighborhoods). Atlanta also has cluster 3, with neighboring clusters 2

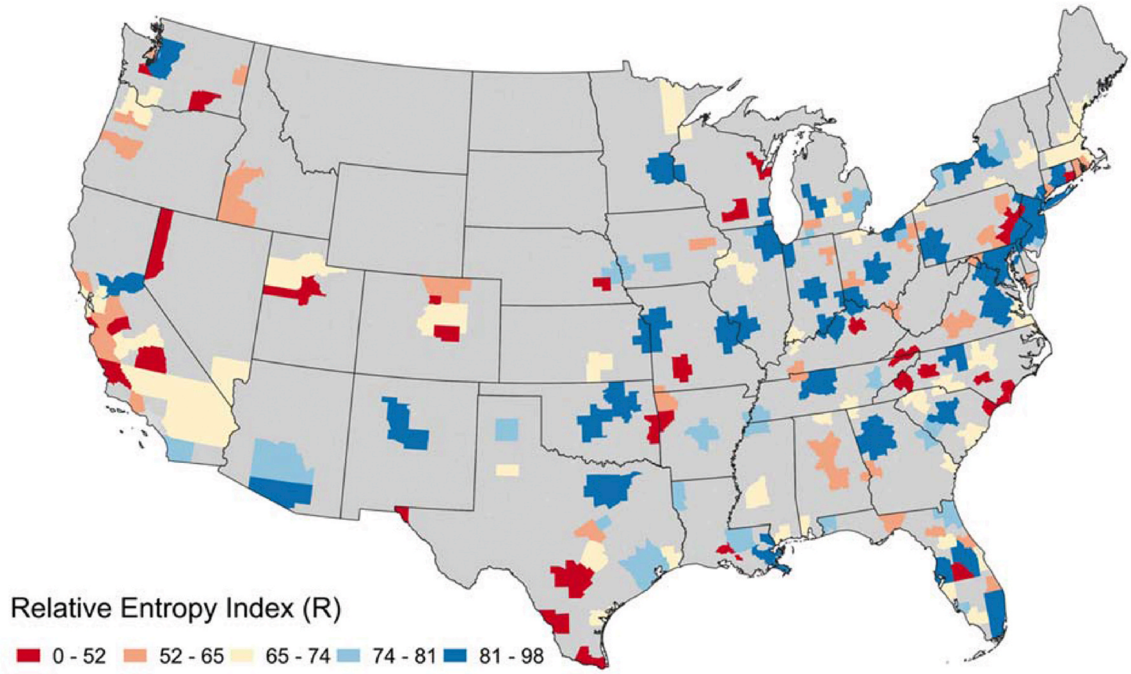

Fig. 3. Intra-metro diversity of clusters (relative entropy index scores per CBSA)
Note: Core-based Statistical Areas (CBSAs) are mapped in the figure, displaying the relative entropy value (R), or index score indicating the diversity of cluster classes present across assigned census tracts within the metro area. R index values range from zero, where there is total concentration of a single cluster, to 100, where the mix of clusters is completely even. The map's color scale is specified using quantile breaks to show a roughly even number of each subset.

and 4; however they are located primarily on the southside, in contrast to cluster 5 (highly-educated; immigrants in high-skilled jobs; homeowners) and cluster 6 (high earning; homeowners in business and tech jobs; high-priced markets) on the northside.

Panels C and D, respectively, include the top and bottom three CBSAs in terms of the percent of total tracts that are shrinking. In these six examples, the CBSA is shrinking as a whole, but that does not necessarily mean that all tracts are shrinking. Toledo, OH (49.3%), Tucson, AZ (36.2%), and Rockford, IL (32.6%) (in panel C) have the highest proportion of shrinking tracts, indicating that shrinkage is spatially distributed across the CBSA—this trend is more prominent in these CBSAs than in Erie, PA (17.6%), Binghamton, NY (20.0%), and Dayton, OH (24.6%) (panel D), where shrinkage is concentrated in a small geographic area of the CBSA. Rockford and Dayton look fairly similar to other midwestern cities, whereas Tucson, AZ reveals a more unique pattern of a north-south split between cluster 6 (high earning; homeowners in business and tech jobs; high-priced markets) and cluster 7 (immigrants; low-skill service sector; renters).

5. Discussion and conclusions

In this study, we offer a taxonomy of shrinking places, that is, an examination of the variegated nature of population decline across the United States. This approach offers an in-depth examination of population loss and associated socio-economic and housing characteristics. Specifically, we show that shrinkage, in terms of population loss, is occurring across a diverse set of locations in the United States. In our analysis, we further show that not only are shrinking places comprised of different demographic groups, but other conditions (e.g., differing levels of economic prosperity and decline, housing quality, and social capital) in these places vary as well. The variation within these shrinking places offers a new and valuable vantage point for academics and policy makers to approach the issues and challenges associated with population loss. The indicators suggest that each cluster should be studied within its specific context to better understand the challenges and demands that each community requires. Additionally, the high resolution of our unit of analysis (census tract), provides a necessary level of detail for examining both inter-regional heterogeneities and intra-regional differences, with contrasting contexts existing within a single metro area. These patterns highlight the historical development and contemporary transition in different parts of the country, as well as the spatial distribution of urban change at a neighborhood scale. For example, some patterns that emerge show tracts tend to group together spatially by cluster class, reflecting processes of residential segregation along lines of race and class (Jargowsky, 2018). However, other patterns indicate broader migration trends and demographic shifts (e.g., aging) that could be irreversible in the short-term. Furthermore, such patterns also capture the range of economic characteristics with few CBSAs containing cluster 6 tracts (high earners, high priced housing markets) with a much broader proliferation of low-skilled, low-income tracts in undervalued neighborhoods. A deeper understanding of the various clusters should offer a starting point for policy makers to evaluate the overall sustainability and resiliency of a region.

Ribant and Chen (2020) identify shrinking cities across the United States, grouping them into seven clusters, according to size and locational context – their definitions included location relative to core/suburban periphery. Their relevant discussion also suggests that their two "small city" clusters are most characteristically different in terms of the causes of shrinkage (e.g., deindustrialization, loss of manufacturing), as well as the current conditions in those places (e.g., whiter, older, more rural, geographically isolated). In contrast to shrinking cities within larger metros, or growing metros, the challenges in these small rural areas are fundamentally different—they are related to things like regional inequality and availability of resources and opportunities for revitalization. While these differences may exist between metro areas, or among cities and towns within a single metro, in this study we offer one further level of analysis by grouping census tracts. This higher resolution of variation that we consider indicates that neighborhood-level differences are present within a city or metro, and are therefore relevant for consideration. As we show in Fig. 3, there is much variability within some MSAs (e.g., Kansas City), that is, a high *relative entropy* index value indicating diversity. While Ribant and Chen separate Kansas City, KS from

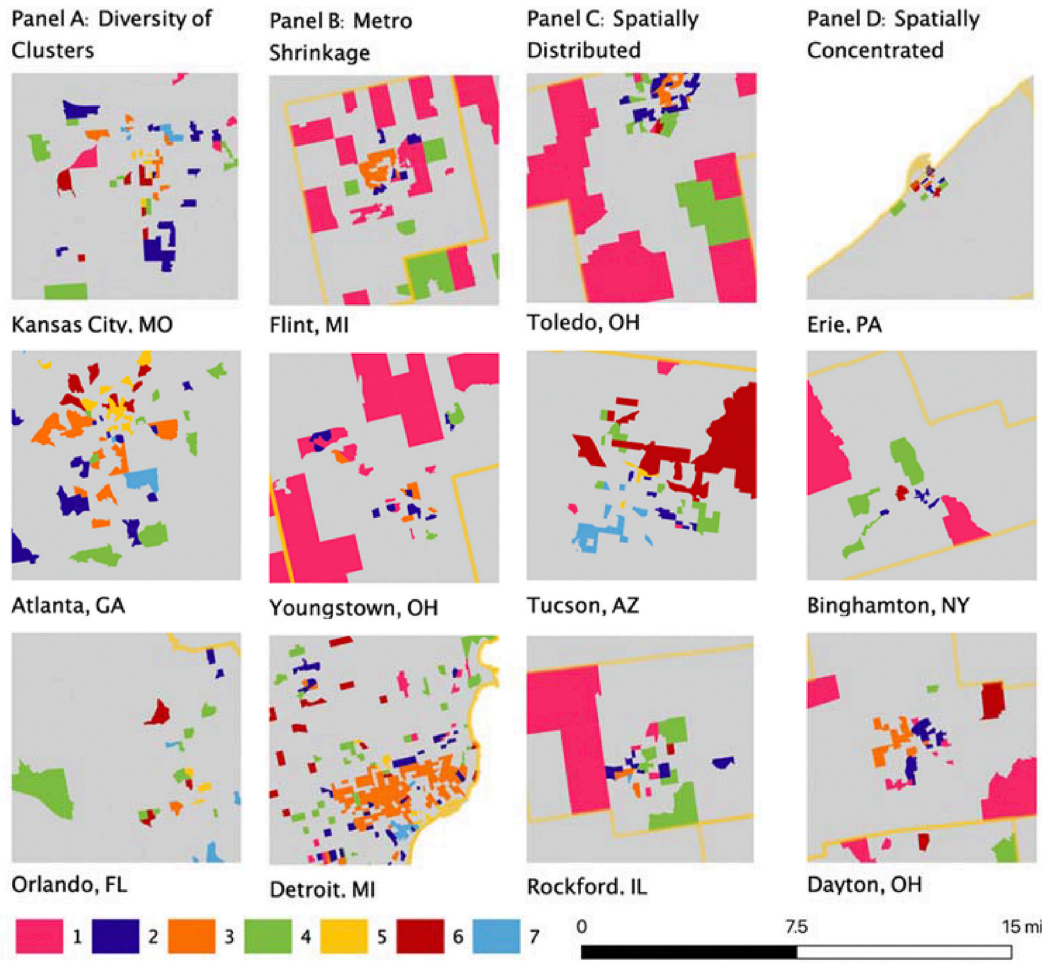

Fig. 4. Intra-metro distribution of clusters (census tract cluster classification, by CBSA)
Note: The map series in the figure display local distribution of census tracts coded by cluster class, within select Core-based Statistical Areas (CBSAs). Cluster IDs are indicated by unique color and correspond to the assigned cluster labels described as follows. Cluster 1: working class; homeowners; Cluster 2: low socioeconomic status; renters; and homeowners; Cluster 3: service sector workers; vacant/undervalued neighborhoods; Cluster 4: highly educated; middle class; homeowners; Cluster 5: highly-educated; immigrants in high-skilled jobs; homeowners; Cluster 6: high-earning; homeowners in business and tech jobs; in high-priced markets; Cluster 7: immigrants; low-skill service sector; renters. CBSA names were abbreviated here to include the primary (core) city/state in the metro area. Panels A-D include the top three CBSAs for each category, organized in rank order from top to bottom in the column layout. Panel A is based on Relative Entropy Index values; Panel B is based on percent population loss for the entire CBSA; Panels C and D are based on the percent of all tracts in the CBSA that were shrinking – higher percentages are considered spatially distributed (panel C), and lower percentages are considered spatially concentrated (panel D).

Kansas City, MO, labeling the former in the group of *culturally transforming* cities, our analysis goes a step further to examine neighborhood level variety showing all seven cluster types within the individual MSA (see Fig. 3, panel A).

Some of the broader findings and implications from this analysis are reviewed below. The largest cluster, by number of total tracts, is cluster 1 (working-class; homeowners), which also happens to be the least metropolitan (smallest proportion of tracts in a large metro area). Geographically the cluster is fairly widespread across eastern census divisions, however it is also the dominant cluster in CBSAs across several Appalachian states as well as other areas such as Oregon and Washington. At the local scale, we see patterns of larger, outlying tracts, which may be more suburban, rural, or former industrial areas. Demographically these areas appear to be older, middle-class, white communities with higher rates of production and manufacturing jobs and lower rates of college education. Cluster 1 appears most distinct from others in terms of both the location and socio-economic profile. Both are relevant given historical and political contexts of communities that may once have been dependent on a single industry or even single company economies, from which jobs have been steadily shed over the last half century. It is therefore important to assess the impacts for local infrastructure, which may be principally tied to 20th century industries like steel and coal, or agriculture.

Ribant and Chen (2020) also identify "small city" clusters, many of which are found in the Appalachian region and former manufacturing regions (Rust Belt*)*. In addition, Weaver (2017) examines decline in the Appalachian region, and discusses the importance of housing stock quality in relation to the impact that business development can have on reversing economic decline. Weaver et al. (2016) review various policy approaches from pro-growth strategies to smart decline and rightsizing. These strategies require local governance to account for existing infrastructure while at the same time planning municipal systems for reduction in population size. Some of these planning efforts involve alternative land use and re-allocation of resources that were originally established for industrial economies of the past. Further considerations are necessary to address the unique issues that these communities face, including those related to the rural location, social and cultural capital, health and aging, or the experience and skill sets of the labor force. Particularly, if decline has been long running, vulnerability to economic shocks may be higher and in turn, will affect the broader region and the US as a whole. Hartt, Zwick, and Revington (2019) consider the importance of innovation and adaptation, along with the role of anchor institutions in facilitating some shrinking cities to transition and prosper in the new century amid economic transformation and significant population loss. One of the key things they identify as central to the success of these places is that they tend to be associated with a more dynamic integration within the broader regional economy.

We identified some of these prosperous places in clusters 4 (highly-educated; middle-class; homeowners) and 6 (high-earning; homeowners in business and tech jobs; in high-priced markets), which are characterized by older homeowners. Therefore, it is possible that the population loss in these clusters could be due to, or associated with aging. Franklin (2021) looks at neighborhoods experiencing population loss, noting that the burden of decline in such places is felt disproportionately by different demographic groups. Similar to cluster 1, these two are also found primarily in the East, though with more representation in New England and Mid-Atlantic, as well as Pacific and Mountain census divisions in the case of cluster 6. They further differ from cluster 1 in terms of having higher income, lower poverty, and more education. Additionally, the types of jobs are very different, centering more in information services than in manual labor. While all three may face similar challenges in terms of the source of population loss (net out-migration and/or aging-in-place/natural decrease), there would be very different outcomes when it comes to short/long-term resiliency and availability of local resources and amenities for navigating continued change. Future studies incorporating in-depth spatial analysis of where clusters 4 and 6 are located within the metro area (suburban communities, transitioning neighborhoods) may be helpful to develop models to understand future needs of the community.

Alongside the prosperous cluster (higher education and income) is cluster 5 (highly-educated; immigrants in high-skilled jobs; homeowners). Cluster 5 is bi-coastal, represented primarily in Mid-Atlantic and Pacific census divisions, with relatively low presence in the East North and South Central census divisions. It is also dominant in only four CBSAs, namely San Francisco Bay Area, CA, Boston, MA, Austin, TX, and Ann Arbor, MI. These are areas with large presences of colleges, college students, young professionals, tech centers and start-up firms. Those localities will have drastically different needs and priorities relative to clusters located in other parts of the country. Further, it is likely that a unique set of anchor institutions (educational, research, healthcare, philanthropic) exists here, offering a different collection of amenities and partners with whom to engage (Hartt, Zwick, & Revington, 2019; Silverman, 2020). While these areas are less likely to be economically stressed, there may be other challenges associated with change such as affordability, displacement, and demand for new/different public services (Cortese, Haase, Grossman, & Ticha 2014; Hollander & Németh, 2011). Patterson, Ranahan, Silverman, and Yin (2017) review the case of Community Benefits Agreements (CBAs), suggesting that the application of such a planning strategy in shrinking cities to address issues of social justice and redistribution of resources amid shrinkage could produce more favorable, equitable outcomes.

From our study, it can be noted that places with more demographically diverse population (cluster 2: low socioeconomic status renters and homeowners), poor African American population (cluster 3: service sector workers; vacant/undervalued neighborhoods), and young Hispanic population (cluster 7: immigrants; low-skill service workers; renters) appear more stressed (higher poverty; lower income; lower housing value, higher vacancy) and therefore are at a risk for economic decline. Clusters 2 and 3 are found in most areas across the South Atlantic, East North, and South Central census divisions. They are also found in small dense census tracts closer to urban cores. These clusters also have high rates of vacancy, and only average rates of homeownership, suggesting that housing infrastructure may be stressed as residents depend on low wage jobs in food services and retail, and what remains of production and manufacturing. Further, if these are communities in larger CBSAs, it is likely that fiscal strains at the municipal level may negatively impact these "inner-city" neighborhoods. This is because municipal budgets are often directed toward financially attractive investments while neglecting neighborhoods that are shrinking. Silverman (2020) discusses these types of patterns in relation to the *dual city* phenomenon of uneven development within a metro area.

Similar to cluster 1 (working class; homeowners), cluster 7 (immigrants; low-skilled; renters) again appears more distinct relative to the patterns of other clusters. Located mostly in the West South Central and Pacific census divisions, as well as being the dominant cluster in large parts of Southern Florida, these are communities with low vacancy, low educational attainment, and mostly food service and production jobs. These areas represent a major locus of regional transition, where new immigrants are establishing themselves and as a result, these areas carry a range of potential opportunities and challenges for developing the resources uniquely required in those communities. Literature on immigration and the trends of foreign-born residents arriving in *gateway cities* outside of traditional big cities has grown in recent years. Some of these studies examine the significance of these new population arriving in places that are shrinking in size (Adhya, 2013; Bagchi-Sen, Franklin, Rogerson, & Seymour, 2020; Bose, 2020; Hackworth, 2021).

The policy solutions indicated in the literature include novel responses to population loss, such as investing in green infrastructure for recreation and supporting aging populations with amenities for retirement. Such efforts serve as an alternative to the growth-only model which continues to be the predominant strategy of local and regional development initiatives. As researchers have shown, the concern for issues of equity, social justice, and sustainability continue to grow in importance. These issues arise not only in the wake of austerity-driven responses (e.g. *rightsizing*), but also as public leaders turn to these alternative forms of development. The value of our work is to highlight that a one-size fits all strategy is unlikely to be effective given the wide variation found in the types of places defined as *shrinking*.

The features of contemporary urban crises are not limited to shrinking places, but perhaps manifest more severely in growing places, where issues of inequality, access, and affordability are becoming widespread (Galster & Lee, 2021; Nijman & Wei, 2020). Therefore, growth and shrinkage need to be examined together when studying places at multiple scales: neighborhood (Mallach, 2015), metropolitan area (Ribant & Chen, 2020; Silverman, 2020; Silverman et al., 2013), and the region (Hirt & Beauregard, 2019). The data that we have examined reveal that patterns of shrinkage across metro areas are non-uniform, and that the *types* of shrinkage vary as well. While the literature on urban growth is much more expansive, additional work is needed to bridge the divide between research on growth and shrinkage (Reis, Silva, & Pinho, 2016). Our work offers a methodology for identifying characteristically different forms of shrinkage. This approach can be used by various stakeholders interested in regional and community development to understand the complexity surrounding population change and its associated outcomes. Future research can focus on shrinkage clusters in metropolitan areas for a nuanced approach to policy development and implementation.

Author statement

Conceptualization: Bagchi-Sen, Karp.
Methodology: Karp, Bagchi-Sen, Rogerson.
Formal analysis: Karp with feedback from Bagchi-Sen and Rogerson.
Writing - Original Draft: Karp, Bagchi-Sen.
Writing - Editing: Bagchi-Sen, Rogerson, and Karp.

Appendix A

We use the k-medoids method to cluster census tracts into unique groups, specifying values for k (number of groups) to evaluate all partitions from $k = 10$ to a maximum k of 10. A visualization of clustering for three values of k (5, 6, 7) is shown in Fig. A.1. The scatterplots present only the first 2 PCs, which demonstrate good separation between each group (shown by unique colors), with slightly more variation apparent in PC1, along the x-axis. K-medoids is a variant of the more commonly known k-means algorithm. We initially analyzed classification using k-means, and compared the two sets of results. k-means seeks to minimize total squared error (distance from the group mean); k-medoids seeks to minimize a distance between each point and a designated center point. Both methods are forms of partitioning. k-medoids has the potential to be more robust to noise and outliers, since it is not dependent on an arithmetic mean. K center points are randomly set, and then iteratively shifted/updated to find the most appropriate group center. An analysis of the Gap Statistic was conducted to compare the relative improvement of incrementally introducing each additional group into the cluster classification. The Gap Statistic peaks at $k = 7$, before leveling off. Values greater than $k = 7$ are shown to not be significantly different, based on a one standard error rule. Based on the k-medoids algorithm, we selected a solution List of variablesfor $k = 7$ to partition the data.

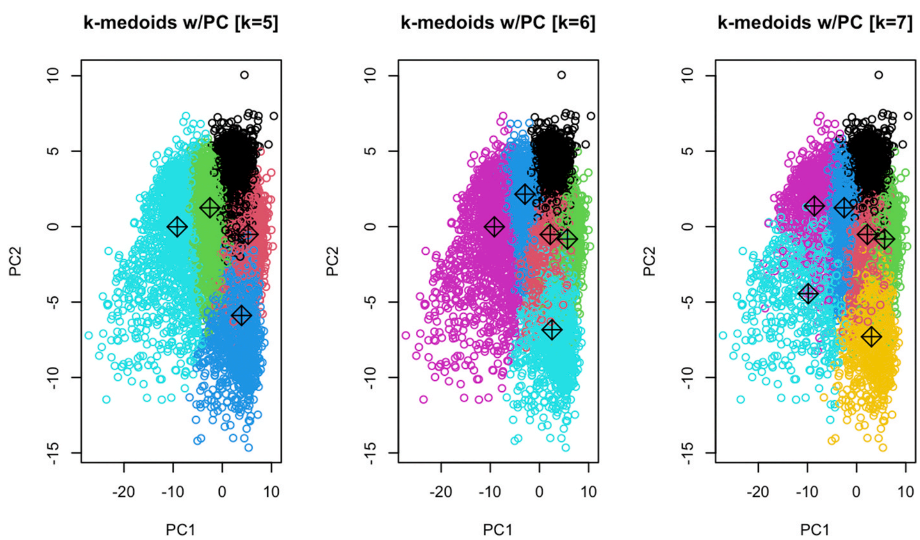

Fig. A.1. Visualization of k-medoids results for three clustering solutions ($k = 5$, $k = 6$, $k = 7$).

Table A.1
List of variables

Population	**Households**	**Education**
Population (2009) (n)	Female-headed (%)	Current HS student w/a job (%)
Pop. (2017) (n)	Living Alone (%)	Educational Attainment (HS) (%)
Pop. Loss (2009–2017) (n)	Living Alone (65+ years old) (%)	Edu. Attain (College/no deg.) (%)
Pop. Change (2009–2017) (%)	Living w/Parents (18–34) (%)	Edu. Attain (Bach deg.) (%)
Pop. Change Quartile (%)	English-only speaking (%)	Edu. Attain (Grad deg.) (%)
Pop. Change Top 50% (%)	Spanish speaking (%)	**Higher Education****: *Undergraduate Degree*
Demographics	Sp./limited English speaking (%)	Degree holder (White) (%)
Median Age	Teenage single mother (%)	Deg. holder (Asian) (%)
White/Non-Hispanic (%)	No computer in home (%)	Deg. holder (Hispanic) (%)
Black/Non-Hispanic (%)	No internet in home (%)	Deg. holder (minority) (%)
Asian/Non-Hispanic (%)	**Income**	Deg. holder (male) (%)
Native Am./Non-Hispanic (%)	Median Household Income ($)	Deg. holder (female) (%)
Multi-racial/Non-Hispanic (%)	Mdn HH Inc. Quartile (%)	Deg. holder female/male ratio
Non-Hispanic (%)	Mdn HH Inc Top 50% (%)	Deg. holder (<40 y/o) (%)
Non-White (%)	Below Poverty line (%)	Deg. holder (male <40 y/o) (%)
Black/Hispanic (%)	Below 200% of Poverty line (%)	Deg. holder (female <40 y/o) (%)
Foreign	HH receive public assistance (%)	Deg. holder (<40 y/o) F/M ratio
Foreign born (n), (%)	HH receive SNAP benefit (%)	**Higher Education****: *Arts & Humanities Degree*
For. born (origin: refugees) (%)	No health insurance (child) (%)	Degree holder (%)
For. born (origin: S. Asia) (%)	No health insurance (adult) (%)	Deg. holder (male) (%)
For. born (origin: W. Euro) (%)	Dual coverage (65+) (%)	Deg. holder (female) (%)
For. born (origin: Mid-East) (%)	Gini Coefficient	Deg. holder female/male ratio
For. born (origin: Cen. Am.) (%)	**Employment**	**Higher Education****: *STEM Degree*
For. born (origin: Mexico) (%)	Unemployment (%)	Degree holder (STEM) (%)
For. born (after 2010) (%)	Not in labor force (%), Military (%)	Degree holder (White) (%)
For. born (prior 2010) (%)	Mean hours worked/week	Deg. holder (Asian) (%)
Median Age of Foreign Born	Self-employed (%)	Deg. holder (Hispanic) (%)
Housing	Public employee (%)	Deg. holder (minority) (%)

(*continued on next page*)

Table A.1 (*continued*)

Housing units (n)	Employed (HS dropout) (%)	Deg. holder (male) (%)
Housing units (per capita)	**Jobs***: *Occupation/Industry*	Deg. holder (female) (%)
Vacancy (%)	Business/Finance (occ.) (%)	Deg. holder (<40 y/o) (%)
Renter Occupied (%)	Comp. Sci/Engineering (occ.) (%)	Deg. holder (male <40 y/o) (%)
Multi-family units (%)	Arts/Entertainment (occ.) (%)	Deg. holder (female <40 y/o) (%)
Mobile homes (%)	Healthcare (occ.) (%)	Deg. holder female/male ratio
Median year built	Food/Maintenance (occ.) (%)	Deg. holder (<40 y/o) F/M ratio
Owner tenure (median year)	Production/Transport (occ.) (%)	Deg. holder minority ratio
Renter tenure (median year)	Manufacturing (occ.) (%)	
Rent <$1000 (%)	Finance/Insurance/Real Estate (ind.) (%)	
Rent >30% income (adult) (%)	Retail (ind.) (%)	
Rent >30% income (65+) (%)	Healthcare (ind.) (%)	
Cost >30% income (adult) (%)	Information Services (ind.) (%)	
Cost >30% income (65+) (%)	Agriculture (ind.) (%)	
Real Estate taxes > $2000 (%)	Median Earn.: Manufacture ($)	
Median Housing Value ($)	Median Earn.: Construction ($)	
Real Estate taxes aggregate ($)	Median Earn.: Retail ($)	
	Median Earn.: Info Services ($)	
	Median Earn.: Fin/Insur/RE ($)	
	Median Earn.: Education ($)	
	Median Earn.: Comp. Prog. ($)	
	Median Earn.: Healthcare ($)	

* Job categories are computed as a percentage of all workers and as a per capita proportion (per 10,000 persons) relative to the total residential population.

** Degree holder categories are computed as a percentage of all college graduates (25+ y/o) and as a per capita proportion (per 10,000 persons) relative to the total residential population.

Table A.2
Top three variables for the first 5 Principal Components (PCs)

Principal Component	Variable Name	Variable Loading
PC 1	Per capita total college degrees	−0.178
	Per capita college degrees for male graduates	−0.177
	Per capita total STEM degrees	−0.172
PC 2	Percent with English only spoken at home	0.215
	Percent non-Hispanic	−0.200
	Percent Hispanic	0.200
PC 3	Percent Black non-Hispanic	0.228
	Percent college degrees for minority race graduates	0.188
	Percent of adults living alone	0.184
PC 4	Percent college degrees for male graduates under 40 y/o	−0.197
	Percent of 18–34 y/o living with parents	0.196
	Percent college degrees for White graduates	−0.171
PC 5	Percent college degrees for graduates under 40 y/o	0.235
	Percent STEM degrees for graduates under 40 y/o	0.226
	Percent college degrees for female graduates under 40 y/o	0.216

Note: The fifteen variables were identified for their importance to each of the associated principal components. Variables loading values were ranked high-to-low, in terms of absolute value, for each PC, and the first three variables are presented here. It is valuable to note that the top three ranked variables for each PC are indicators of demographic, educational, and family household characteristics. However, all variables are represented in each PC even if only to a lesser degree.

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