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A typology of U.S. metropolises by rent burden and its major drivers

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Abstract Scholarly work on rent burden, a rather scantily discussed topic within the broader realm of declining housing affordability, still lacks a firm theory. This article seeks to address this gap by developing a typology of U.S. metropolises which centers on their rent burden status and serves as an initial step toward theory building. We employ principal component and cluster analyses to identify seven distinct types of metropolises and their potential drivers of rent burden. An examination of these seven types suggests that rent burden has spatial randomness to it, since some metropolises in the seven types do not confine to specific geographies. Metropolises with pronounced specializations in education/medicine, information, and arts, recreation, and entertainment exhibit higher rent burden, whereas older Rust Belt metropolises have lower burden. Interestingly, emerging new-economy metropolises exhibit lower rent burden as well, likely reflecting the benefits of newer housing and a diverse economic base. Finally, rent burden, besides being an outcome of the housing demand/supply mismatch, is also a manifestation of income potentials that are affected in complex ways by local labor markets and regional economic specializations.

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Introduction

Increased rentership in the U.S. since the Great Recession (Seymour & Akers, 2021; Wachter, 2015) along with significant population shifts over recent decades both have made rent burden intense and widespread across America (Colburn & Allen, 2018; Dawkins & Jeon, 2018; Edmiston, 2016). By 2015, almost half of U.S. tenants paid more than 30% of their household income for rent (Gabriel & Painter, 2020). The extent of rent burden has been intensified by increased activities of institutional investors and corporate landlords within the rental market (Christophers, 2021; Pfeiffer et al., 2021; Raymond et al., 2018), giving rise to the phenomenon of rental housing financialization targeting single-family rentals in suburbs as well as apartment buildings in denser urban cores (Fuller, 2021; Teresa, 2016). However, what types of metropolises suffer from higher levels of rent burden, and how might that be associated with their socioeconomic and other determinants? This article addresses these questions by developing a typology of rent burden for U.S. metropolises using the framework of regional economic specializations and coupled with other socio-spatial characteristics. While being a timely addition to geographic knowledge and a broader scholarship, our typology aims at illustrating various facets of rent burden and similarities/differences among U.S. metropolises regarding the intensity and potential drivers of rent burden.

To the best of our knowledge, no research has yet developed a typology of rent burden and its potential drivers, or even a typology of housing cost burden—a better studied phenomenon focused on homeownership. Our typology of 380 U.S. metropolises could help inform scholars and policymakers when devising and implementing better solutions to address rental housing unaffordability stemming from different reasons across diverse locations. This typology will also advance geographical knowledge by providing a spatially-oriented inventory of metropolises classified by rent burden drivers while using GIS and cluster analyses.

Background

Rent burden definition

Scholars and policymakers often designate a household as rent-burdened if it pays 30% or more of household income toward rent (Collinson, 2011; Joice, 2014). Some may argue that the U.S. Census Bureau provides an "official" measure of housing cost burden in their data. However, another issue stems from that—whether the agreed upon definition has empirical support. While some scholars (e.g., Newman & Holupka, 2014) provide empirical support for the 30-percent threshold, its usage was questioned and challenged by others (e.g., Bramley, 2012; Samarin & Sharma, 2021) as crossing the 30-percent threshold may be quite common in numerous unaffordable locations (see examples in Metcalf, 2018). An alternative perspective on housing affordability is the residual-income measure which highlights the interaction among incomes, housing costs, and the costs of non-housing necessities (see Stone, 2006). Since this article deals with spatial divisions, rather than households, and due to the lack of aggregate data, we only acknowledge this alternative concept.

In this article, to better capture rent burden's extent, we include both abrupt (30-percent threshold) and continuous (rent as a percentage of income) variables to design a composite measurement—rent burden index (RBI)—which bridges the two approaches and attains higher precision in illustrating rent burden's variations across U.S. metropolises (see subsection "Methodological Steps" for further details).

Rent burden drivers in housing scholarship

Rent burden—often being overshadowed by terms such as housing cost burden or housing stress—has multiple potential determinants. Demographic characteristics including race/ethnicity and foreign-born populations (also immigration and legal status issues) have been examined for their relationships with housing cost burden and, on seldom occasions, with rent burden (Allen, 2022; Desmond, 2018; Elmelech, 2004; Greulich et al., 2004; Hess et al., 2022; McConnell, 2013; Mimura, 2008; Rosen et al., 2022; Sharma & Samarin, 2023). Some of these studies, for example, found that immigrants from developing countries and undocumented immigrants both suffer from higher housing cost and rent burden compared to U.S.-born minority counterparts. Similarly, disadvantaged minorities, particularly Blacks and Latinx, are more affected by rent burden (ibid). However, some immigrant groups may experience lower rent burden (compared to other low-income groups) because of living in multigenerational or multifamily households, thereby increasing their aggregate household income relative to rent.

Other demographic characteristics affecting rent burden include the life course, age, marital status, presence of children, household size, single parenthood, and gender, to name a few (Colburn & Allen, 2018; Coley et al., 2014; DeVaney et al., 2004; Leventhal & Newman, 2010; Moore & Skaburskis, 2004; Nelson et al., 2013; Sharma, 2023a). Since children's development and housing affordability are intertwined (Leventhal & Newman, 2010), a stage within the life course may correspond strongly with rent burden's intensity (Moore & Skaburskis, 2004) in a way that it might be higher for single and single-parent households compared to childless couples (DeVaney et al., 2004), and much higher for larger households, especially those with children (Colburn & Allen, 2018) as well as those single-female-headed households (no spouse) with children living in poverty (Sharma, 2023a). Additionally, housing cost burden has a negative association with marital satisfaction, since households with a fully paid-off mortgage tend to demonstrate higher levels of marital satisfaction (Nelson et al., 2013).

Other scholarship on housing cost burden has examined housing-induced poverty issues with a focus on economic hardships, well-being, and savings behavior (Deidda, 2015; Mendenhall et al., 2014; Shamsuddin & Campbell, 2022; Warren, 2018). Stemming from housing-induced poverty comes the nexus between housing and health (Bowen & Mitchell, 2016) and, more importantly, relationships between housing affordability and access to healthcare (Elliott et al., 2021; Meltzer & Schwartz, 2016). Higher housing cost and rent burden provoke worse health outcomes, since burdened tenants very likely postpone or completely neglect their health needs due to financial strains. In this regard, Samarin and Sharma (2021) documented that in Shelby and Davidson counties (TN), a lack of medical insurance was a common feature of rent-burdened households.

The extent and intensity of rent burden are also attributed to lower housing vacancy rates and an inadequate supply of low-income housing. Indeed, the U.S. has experienced a reduced supply of affordable rentals (Collinson, 2011; Garboden & Newman, 2012; Immergluck et al., 2018; Myers et al., 2021) coupled with difficulties in preserving smaller, lower-cost units, particularly due to landlords' reluctance in keeping rentals affordable and skepticism of large property owners when it comes to developing cheaper housing. Lesser-studied aspects of the built-environment's relationships with housing affordability include buildings' age (Palm, Raynor, & Warren-Myers, 2020) and overcrowding (Sunega & Lux, 2016).

In the American context, transportation is also inextricably linked to housing affordability. Scholars have argued that housing costs should be examined together with transportation costs (Haas et al., 2016; Liu et al., 2021). Housing costs and transportation costs combined together may provide a better picture of affordability as some households may be forced into longer commutes to reduce housing costs, whereas others might tolerate higher rents to mitigate transportation costs (Gober et al., 1993). Additionally, parking fees in America are often included in rents (Gabbe & Pierce, 2017), which further exacerbates rent burden; however, many low-income households, especially in inner-city neighborhoods, do not necessarily own automobiles (Samarin & Sharma, 2021).

Higher Gini coefficients—meaning less income equality—associate with an increase in rent-burdened households (Dong, 2018). Higher income inequality aggravates unaffordability among low-income families because the presence of high-income groups inflates housing prices and simultaneously reduces low-cost options (Matlack & Vigdor, 2008). Finally, educational attainment, often used in studies concerning multiple other phenomena, is one of the major drivers of housing cost and rent burden (Lee & Ahn, 2013; Samarin & Sharma, 2021; Susin, 2007). Generally, higher educational attainments in a metropolis and the greater presence of more educated cohorts both increase housing prices, thus making rentals less affordable for low- and moderate-income groups. At the same time, higher educational attainments at the individual level reduce the incidence of rent burden among more educated people due to their higher income potentials.

Other research documents that many U.S. households, especially those in which the head of a family is engaged in less remunerative employment, suffer from greater financial hardships despite their full-time engagement in specific occupations (e.g., education), and this restricts their economic well-being, especially if they are female-headed households (Sharma, 2023b). In a county-scale analysis of the association between STEM (science, technology, engineering, and mathematics) and other professional disciplines and earnings potentials/economic well-being, Sharma (2023b) found that women, despite their higher educational attainments, suffer from a double penalty as many end up working part-time in order to engage in care activities. A similar study (Sharma, 2023a) found that single female-headed households with children are more susceptible to living in poverty because of the double penalty of being able to work part-time only (also referred to as the motherhood penalty). Thus, females especially suffer from lower incomes which make them more prone to poverty and then rent burden.

The reviewed research, while not necessarily focusing on rent burden (instead, housing cost burden) and/or not being carried out through a geographical perspective, provides a valuable background and helps rationalize the selection of variables. In our typology, we include these characteristics along with occupational specializations the role of which is discussed below.

Role of occupational specialization

Regional labor market characteristics may affect the vitality of housing markets (Andrew, 2012) and rent burden's intensity. Thus, a holistic analysis of housing affordability should include labor market characteristics (Beenstock et al., 2021). Quercia et al. (2002) analyzed relationships between high-tech economic growth and housing problems using a sample of moderate-income and working-class families in major U.S. metropolises. They illustrated that the presence of a sizable high-tech sector decreases housing affordability for such populations. Chapple et al. (2004)'s evaluation of how employment patterns affect housing markets found that the presence of start-ups have a positive effect on housing price appreciation (i.e., higher property values).

A diverse industrial structure promotes economic stability and resilient growth that both form a safety net against unprecedented market shocks (Brown & Greenbaum, 2017; Chen, 2020). In contrast, metropolises with less diverse industrial structures, largely comprising conventional and non-innovative industries, have fewer employment opportunities. This makes such metropolises more vulnerable to prolonged economic distress and also less attractive for current/prospective residents, which may eventually result in lower rent burden. Landis et al. (2002)'s examination of the nexus between industrial structures and housing found that housing market outcomes were affected by a metropolitan industrial structure, and increased housing prices in new-economy metropolises reduced affordability for low- and moderate-income renter households.

Gober et al. (1993) analyzed the incompatibility between expensive housing and low-wage jobs in a highly-specialized town of Sedona (AZ) with concentrations of low-paid service jobs (tourism, arts, and entertainment) catering to affluent residents and visitors. They found that most employees in their sample resided outside of Sedona because of unaffordability and thus had longer commutes; in contrast, those living in Sedona paid substantial shares of their income for rent/mortgage.

Despite informative findings in this scholarship, the effect of regional economic specializations on rent burden has not been acknowledged. In two recent studies, however, rent burden was analyzed in contrasting locations—hot/cold housing markets (Samarin & Sharma, 2021) and growing/shrinking cities (Seymour, et al., 2020). Samarin and Sharma (2021) attributed the difference in rent burden determinants in the cold housing market of Memphis and the hot/tight housing market of Nashville to the varying labor market conditions and economic specializations. Likewise, Seymour et al., (2020) found complex dynamics between incomes and rents in shrinking cities. Specifically, in growing cities, rent burden was intensified since rents increased faster than incomes, whereas in shrinking cities declining incomes were caused by economic contraction.

Rent burden and community opposition to housing development

While the drivers of rent burden have been discussed above, scholars have suggested that one of the best ways to reduce rent burden is to construct more housing (Monkkonen & Manville, 2019). For example, Houston—the fourth largest metropolis in the U.S.—had its 2018 inflation-adjusted housing costs being lower than in 1980, despite the city comprising many more residents, thence achieving "extraordinary affordability" by easing regulatory and bureaucratic barriers to new construction (Durning, 2017). Another example is Tokyo that adopted flexible zoning, fewer legal obstructions, minimal red tape, all of which succeeded in keeping its median housing values at around \$300,000 as against \$748,000 in Seattle in 2018 (ibid).

Numerous scholars have focused on community opposition to affordable housing manifested in the NIMBY (not-in-my-backyard) attitude toward low-income housing which has been likened to a potential increase in crime, lowered property values, "undesirable" populations, increased traffic congestion, and animosity toward developers (not necessarily newer developments per se). The latter is especially the case when developers are expected to earn large profits coupled with changes in neighborhoods' characters and aesthetics, strained public services, and fears of local residents in terms of facing various issues (Monkkonen & Manville, 2019; Tighe, 2010). In the U.S., there is an unwelcoming attitude to the poor and minorities, with widespread negative sentiments toward the recipients of public program benefits—adding to the opposition to such affordable developments (Tighe, 2010). Despite significant progress in public opinion toward racial minorities, especially Blacks, and being open to residential and institutional integration as a demonstrative symbol of racial equality, most Americans do not truly embrace economic and/or class integration (ibid). Most are still divided by their attitudes toward government's intervention in numerous policies that cater to equality/equity projects to ensure a better treatment of minorities. Despite such opposition, Tighe (2010) finds that once developed, neighbors tend to have fewer complaints about their new neighbors or new homes. The author suggests numerous ways of coping with public opposition to affordable housing including managing opposition through planning, educating about the proposed projects, marketing of those projects, negotiating with neighbors regarding the aesthetics and size of new developments, and consensus building.

While rent burden has remained a long-term problem in college towns, recently they have been the focus of news media, especially in the wake of the return-to-school for in-person learning. Increased rent burden among college students forced many into taking extra loans, working 20–30 h/week despite being enrolled as full-time students, delaying return to college, moving back to their hometowns, overcrowding/sharing their apartments with more roommates (Hatch, 2022), and cutting down on non-essential items and compromising with their lifestyles (Juv Consulting). Since 2020, rents have soared by 24% around the University of North Carolina at Chapel Hill, by 31% in Tempe (Arizona State University), and by 36% in Knoxville—home to the University of Tennessee (CBS Miami). Reasons for such price increases include limited newer construction since the recession of 2007–2009, COVID-19, and the Ukraine-war-induced recession. Additionally, expensive apartments located in and around college campuses oftentimes come with extra/luxurious amenities that students do not really need (Juv Consulting). Finally, median rents in 50 largest metropolises hit a high of $1,575 by June 2021—an 8.1% increase from June 2020 (ibid). Such an increase can be especially problematic for student populations.

Typology of metropolitan-level rent burden

The reviewed scholarly work and some identified gaps all call for a need to create a typology of rent burden for metropolises while considering a set of phenomena—regional economic specializations, demographics, socioeconomic status, built-environment, and housing. This typology, representing bundles of numerous characteristics, will help better understand rent burden, its potential drivers and/or consequences, and geographies of rent burden types across the nation. By designing this typology, we contribute to establishing a theoretical framework for future research on relationships between rental housing affordability and a wide range of socioeconomic phenomena, especially occupational specializations which lack in existing research.

In short, a typological analysis is a tool for examining descriptive quantitative/qualitative data whose end goal is to create a set of related and yet distinct categories (i.e., types) within a phenomenon that differentiates across the phenomenon. Thus, typologies imply categorization and are devoid of hierarchical arrangements (Ayres & Knafl, 2008). Typologies are also viewed as a method of simplification when a larger dataset is being reduced to fewer meaningful groups. This technique uncovers relationships within a phenomenon or between several phenomena by disentangling their essence and complexities (Mikelbank, 2004).

A typological analysis has been used for studying urban phenomena, morphologies, and processes such as sprawl categories (Sarzynski et al., 2014) or the spatial structure of employment in U.S. metropolises (Hajrasouliha & Hamidi, 2017). Typologies with smaller geographies comprising metropolises include shrinking cities (Ribant & Chen, 2020), suburbs (Mikelbank, 2004), inner-ring suburbs (Charles, 2018; Hanlon, 2009), immigrant neighborhoods (Vicino et al., 2011), and neighborhoods experiencing socioeconomic ascent (Owens, 2012).

The process of creating typologies is an important step for theory development (Owens, 2012). This method can generate valuable insights, especially for new knowledge on a phenomenon. Typologies enable scholars to study phenomena using multiple factors, examine how those factors fit together in types, thus offering a more holistic approach to understanding a particular phenomenon (Shepherd & Suddaby, 2017). Typologies offer non-monotonic functions in relationships between independent and dependent variables, thus allowing to go beyond the linear while examining multiple patterns (Shepherd & Suddaby, 2017; Weustenenk & Mingardo, 2023). Given the lack of a solid theory or a framework on rent burden within housing scholarship, as documented in Sharma and Samarin (2022), our typology contributes towards establishing a theoretical framework by addressing the inconsistencies in defining rent burden while also incorporating regional and other socio-spatial characteristics necessary for studying rent burden geographies in a comprehensive manner.

Research design

Scale of analysis

This study examines all the conterminous U.S. metropolitan statistical areas (MSAs) which are a single county or a group of counties delineated by the U.S. Office of Management and Budget based on population size and commuting patterns centered on a core county of each MSA (see U.S. Census Bureau 2). We use MSAs since rentership is predominantly an urban type of housing tenure (Gilbert, 2016). MSAs are also an optimal spatial division for our typology since many suburbs and suburban counties have witnessed a significant rise in single-family rentals (Charles, 2020; Immergluck, 2018; Raymond et al., 2018).

For a better understanding of the genesis of rent burden in locations with varying conditions in economy and housing, it is important to examine MSAs with disparate trends in terms of housing markets. Existing scholarly work has primarily focused on major and most expensive cities. Such skewed focus calls for expanding the housing-related research beyond notoriously unaffordable locations (examples in Metcalf, 2018) while also including *second-tier* MSAs (terminology from Kalafsky & Graves, 2020) as they may also exhibit heightened rent burden. Hence, our research includes all conterminous U.S. MSAs (n = 380).

Data

We use the 5-year estimates from the American Community Survey (ACS) 2015–2019 as our main source of variables. The selection of variables is largely based on theoretical grounding, whereas a few are included due to their intuitive appeal and interest, instead of a firm theory. Sarzynski et al. (2014) used such exploratory reasoning when developing their typology of sprawl in the U.S. Thus, we include population density and high school dropout rate whose consideration seems logical. Additionally, to capture the economic dynamism of an MSA, we use percent change in real GDP from the U.S. Bureau of Economic Analysis.

To quantify rent burden for the ensuing statistical analyses and examination of MSAs' types, we compute RBI which is a compromise between two single-variable approaches (e.g., Seymour et al., 2020; Samarin & Sharma, 2021). RBI is the mean of two normalized variables: (i) rent as a percentage of household income and (ii) the share of households paying more than 30% of income toward rent. Since RBI attains higher levels of precision by incorporating those two rent-burden-related variables, this metric is expected to be more rigorous compared to utilizing a sole variable. While being an integral part of our statistical analyses, RBI is mapped and serves as a benchmark for interpreting MSAs' types.

Regarding the original variables based on which RBI is computed, we conjecture that for such a large scale of MSAs (not census tracts or census block groups with high margins of error) variables used to calculate two rent variables are basic, readily available, and rather easily estimated by the Census. We additionally emphasize that in this article, the 5-years estimates are used to discuss rent burden as a long-term issue, not the most recent rental markets' volatility pertaining to COVID-19. Additionally, there were no substantial changes at the metropolitan level during several years prior to the pandemic which would have undermined the 2015–2019 estimates of the two rent variables serving as a foundation for RBI.

The ACS's employment data by occupations serves adequately for capturing regional economic specializations and industries' agglomerations. For quantifying specializations, we calculate the location quotients (LQs) for employment in select industries. LQs illustrate concentrations of industries in terms of economic output or employment by occupations as well as other phenomena (Moineddin et al., 2003; Slaper et al., 2018). In this analysis, LQs for occupations help interpret rent-burden-centered types of MSAs. LQs above 1 imply that an industry is overrepresented in a particular location compared to the entire study area. The select industries include: (i) manufacturing; (ii) information; (iii) finance, insurance, real estate, and leasing; (iv) educational services, healthcare, and social assistance; (v) arts, entertainment, recreation, accommodation, and food services; and (vi) public administration.

Methodological steps

Calculating variables

We normalize the two rent-burden variables on a 0–100 scale using the following expression before computing RBI:

$$Z_i = \frac{X_i - X_{min}}{X_{max} - X_{min}} \times 100$$

where Z_i—normalized value; X_i—pre-normalized value; X_{min} and X_{max}—lowest and highest values of a variable. After normalization, we calculate RBI using the methodology from De Muro et al. (2011) resembling the human development index. RBI is computed using the formula:

$$RBI = \frac{Z_{rpi} + Z_{m30}}{2}$$

where Z_{rpi}—normalized median gross rent as a percentage of income; Z_{m30}—normalized shares of renter households paying more than 30% for rent (we adhere to the definition of the phrase "median gross rent" from this source: U.S. Census Bureau 1). Then, we compute LQs of six industries mentioned above using the following expression:

$$LQ_i = \frac{e_i/e}{E_i/E}$$

where e_i—MSA's industry employment; e—MSA's total employment; E_i—U.S. industry employment; E—U.S. total employment.

Principal component analysis

Our typology comprises two consecutive steps—a principal component analysis (PCA) followed by a cluster analysis. Such sequencing is a common procedure adopted from studies with different typologies of spatial units (e.g., Hanlon, 2009; Owens, 2012). Instead of using variables themselves for creating our typology, we follow prior scholarly work in urban geography and first conduct PCA (Hajrasouliha & Hamidi, 2017; Hanlon, 2009; Owens, 2012; Sarzynski et al., 2014; Vicino et al., 2011). This data reduction technique has been applied for designing typologies based on a wide variety of phenomena. When extracting components, while the cutoff for Eigenvalue remains at researchers' discretion based on their data's features, studies have often used Eigenvalue of one-and-above and retained these components for further analysis (Du Toit & Cilliers, 2011; Owens, 2012; Sharma & Brown, 2012). In our research, we perform PCA and extract components with Eigenvalue of two-and-above (Hanlon, 2009). The obtained loadings—six PC scores for 380 MSAs—serve as variables for ensuing steps.

Cluster analysis

For developing an original typology, we employ a cluster analysis. PC scores are classified into types using k-means clustering. This technique performs an iterative procedure that groups observations according to their similarities in terms of means of PC scores. The word "cluster" here does not mean spatial clustering; instead, groupings are assembled based on their close values of PC scores. K-means clustering assigns *n* objects into *k* clusters, and each observation is allocated to a cluster with the nearest mean (i.e., minimizing intra-cluster variance). In other words, this technique generates *k* distinct clusters with the greatest difference possible between them given a pre-designated number of output clusters (Ribant & Chen, 2020). Since the k-means approach requires specifying the number of clusters to be created, we intend to identify four-to-seven types to be able to provide meaningful names for the software-generated clusters. Such ballpark of types can be found in several studies (Charles, 2018; Hajrasouliha & Hamidi, 2017; Hanlon, 2009; Ribant & Chen, 2020; Sarzynski et al., 2014; Vicino et al., 2011). However, some have a higher number of types—eight (Owens, 2012) or ten (Mikelbank, 2004).

After conducting PCA, we initially specified five clusters/types. Although several readily interpretable clusters emerged from that specification, there were two large clusters with some MSAs within them differing significantly in terms of numerous variables. This issue persisted in the six-cluster iteration, but with only one questionable cluster. Since there is no rule regarding how many types should be in a sample, the choice of the number of clusters is the responsibility of a researcher (Ahlquist & Breunig, 2012). To avoid cluster redundancy necessary for a useful, meaningful typology (Hedlund, 2016), we finalize our search with the 7-cluster specification, since its results make the most sensible interpretations and serve appropriately for mapping purposes.

Finally, when closely examining our data to come up with better types, we found that the 8-, 9- and 10-cluster specifications produced results that could not be explained in an analytically meaningful way. Interestingly, the 9-cluster specification was especially unreliable since it assigned to one of the clusters only two adjacent MSAs. Given our in-depth review of literature on rent burden and typology analysis, for the sample of 380 MSAs we finalize the empirical threshold for the k-means technique to be a 7-cluster specification.

Results

Principal component analysis

Six components with Eigenvalue above two (Table 1) cumulatively account for 69.04% of variance in our dataset. We use a cutoff value of ± 0.35 (Sharma & Brown, 2012) to emphasize important loadings in each component. The PC output table is provided to justify our selection of variables for the comparison of types. In this article, we abstain from naming principal components (which are not real phenomena but different dimensions in our data) and from providing their detailed characteristics due to the redundancy of such narrative for this analysis, since PCA here is only a preliminary technique; instead, for an easier interpretation of PCA, we embolden those variables above-and-below of the cutoff. As an example, we only describe PC-I. It captures densely-populated metropolises with a specialization in information, with higher housing prices, higher shares of Asian and foreign-born populations, and longer commutes. In PC-I, there is also lower poverty and high-school dropout rates, but higher shares of people with a bachelor's degree, having health insurance, and earning higher incomes.

Cartographic and typology analyses

The purpose of RBI in this article is three-dimensional. It (i) illustrates geographies of rent burden in the U.S., (ii) serves as one of the variables in PCA, and more importantly (iii) performs as a benchmark for interpreting types. The most apparent spatial pattern (Fig. 1) is the concentration of numerous high-RBI MSAs in the Northeast megalopolis, Florida, California, Oregon, and Colorado. Besides notoriously expensive MSAs, there are other notable cases in Indiana, Michigan, and especially the South (Virginia, the Carolinas, Georgia, Louisiana, and Texas). These patterns suggest that rent burden is not an exclusive issue of traditionally-studied unaffordable housing markets of the West Coast or the Northeast; instead it is geographically dispersed and largely defined by local conditions.

Typologies in geography are particularly valuable for their ability in revealing similar cases (of rent burden and its potential drivers here) scattered across different locations. In the typology map (Fig. 2), there are some visible outliers. Likely, the larger a type, the more outliers it has. However, since our typology includes 35 variables that are generalized (i.e., PC scores), we believe some counterintuitive cases assigned to a cluster may be exhibiting similarities in terms of select characteristics, whereas reasons for their higher rent burden (or lack thereof) may be similar to other MSAs within that cluster. For readers' reference, the connection between PCA output (Table 1) and the typology resulting from k-means clustering (Fig. 2; Appendix A) is not straightforward. That is, if PCA identifies 15 components and a researcher extracts six, this does not mean that the number of types should/must be six (see Hanlon, 2009; Owens, 2012).

To get a sense of each type's characteristics, Appendix A juxtaposes means and medians of 20 (out of 35) variables for each type and all MSAs. Selection criteria for such variables are: (i) those demonstrating PC loadings of-and-above 0.35 or of-and-below -0.35 in at least two components (except income inequality represented by Gini coefficient); (ii) occupational specializations appearing once in six components with loadings of-and-above 0.35 or of-and-below -0.35; (iii) variables with loadings above 0.90; and (iv) authors' discretion to include a proxy of housing supply (percent housing units built during

Table 1 PCA output and variables used for designing the typology. Each variable is represented by its PCA loadings for six components with Eigenvalue of two-and-above

	PC-I	PC-II	PC-III	PC-IV	PC-V	PC-VI
Demographics						
Percent White	−0.235	−0.228	−0.148	**−0.875**	−0.077	0.001
Percent Black	−0.118	−0.150	0.063	**0.917**	0.090	0.023
Percent Asian	**0.797**	0.207	0.201	0.111	−0.057	−0.057
Percent Hispanic/Latino	0.037	**0.909**	0.100	−0.123	0.039	0.039
Percent foreign-born	**0.538**	**0.751**	0.108	−0.003	−0.040	0.100
Median age	−0.057	−0.283	**−0.594**	−0.096	−0.343	**0.534**
Family structure						
Percent married	0.055	0.002	**−0.719**	**−0.477**	0.240	−0.160
Average household size	0.029	**0.869**	−0.046	0.183	0.214	0.116
Percent families with children	−0.234	**0.771**	−0.309	0.253	0.081	−0.176
Percent children with single parents	**−0.509**	0.061	0.078	**0.618**	**−0.362**	0.174
Socioeconomic						
Unemployment rate	−0.252	**0.393**	0.091	**0.515**	−0.217	0.264
Poverty rate	**−0.466**	0.093	**0.710**	0.151	0.008	0.267
Income inequality (Gini coefficient)	0.025	0.115	**0.503**	0.318	−0.070	**0.453**
Percent with a bachelor's degree	**0.702**	−0.296	0.214	−0.170	0.263	−0.028
High school dropout rate	**−0.364**	0.079	**−0.456**	0.097	−0.004	0.183
Median household income	**0.885**	0.029	−0.191	−0.144	0.027	−0.158
Percent households with no vehicle	0.024	−0.285	0.069	0.121	**−0.792**	0.048
— — with no health insurance	**−0.376**	**0.558**	−0.024	0.155	**0.427**	0.127
Specializations and economic dynamism						
LQ manufacturing	−0.141	−0.214	−0.179	0.023	−0.197	**−0.489**
LQ information	**0.666**	−0.113	0.068	0.026	0.032	0.035
LQ finance	0.319	−0.163	−0.137	0.077	0.035	−0.004
LQ education and medicine	−0.105	−0.331	**0.740**	−0.213	−0.212	0.056
LQ public administration	−0.069	0.087	−0.122	0.257	0.074	−0.048
LQ arts, entertainment, and recreation	0.050	0.026	0.040	0.021	0.207	**0.752**
Percent employed in private sector	−0.093	0.161	**−0.422**	0.163	−0.058	−0.187
Percent change of real GDP, 2017	0.295	−0.159	−0.078	−0.113	**0.423**	0.094
Housing and built-environment						
Rent burden index	0.275	0.225	**0.357**	0.110	−0.100	**0.611**
Median house value	**0.856**	0.243	−0.012	−0.120	0.056	0.161
Vacancy rate	−0.300	−0.032	−0.212	0.097	0.015	**0.699**
Percent renter-occupied housing units	0.265	0.316	**0.671**	0.268	0.144	−0.168
Percent 0.51 + occupants per room	0.261	**0.882**	0.097	−0.013	0.165	0.016
Median year housing built	−0.020	0.222	−0.061	0.127	**0.845**	0.253
Percent housing units built in 2010–19	0.000	0.046	0.034	−0.006	**0.808**	−0.033
Population density	**0.603**	0.145	−0.061	0.250	**−0.368**	0.037
Average commute	**0.542**	0.206	−0.325	**0.411**	−0.138	0.179
Eigenvalue	6.277	5.642	4.216	4.241	2.639	2.147
Percent variance explained	17.935	16.120	12.046	9.260	7.540	6.135
Percent cumulative variance explained		34.055	46.101	55.361	62.901	69.036

Italicized variables specifically indicate data for renter-occupied housing units

Bolded cells emphasize loadings of-and-below -0.35 and of-and-above 0.35

Rotation converged in 11 iterations

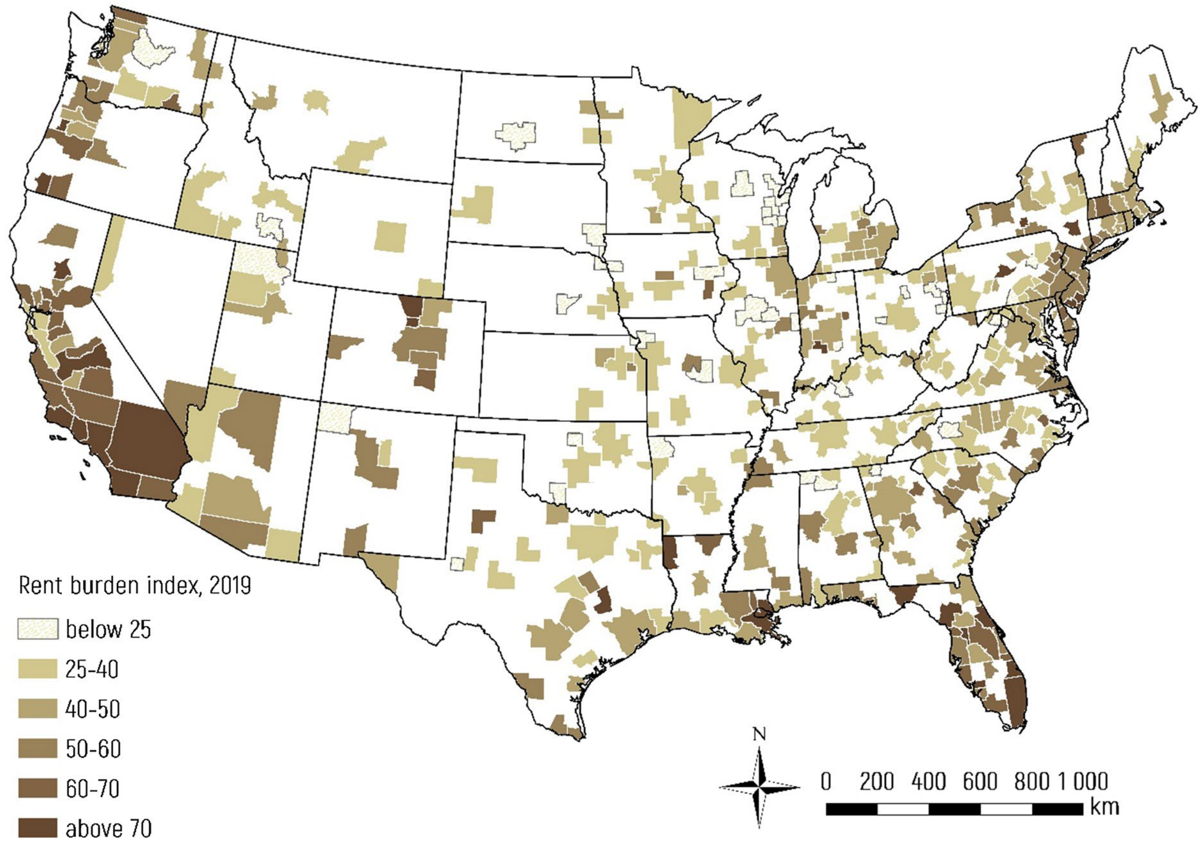

Fig. 1 RBIs of the conterminous U.S. MSAs. Own work based on authors' calculations

2010–2019 in total housing stock), population (not in PCA), and household size to understand a predominant MSA size and a family model in each type.

Type 1: college towns

Despite having relatively large shares of newly-constructed housing units (2010–2019), these MSAs demonstrate the second-highest RBIs, slightly behind Type 7, but much higher compared to all MSAs. This type's MSAs are sporadically located across the U.S. and are represented by second-tier MSAs with large-enrollment universities. College towns are the smallest type by population size, they have the highest poverty rate (this may be a statistical mirage since "low-income" college students oftentimes have other sources of income that are not captured by the ACS—loans, scholarships/fellowships, and family support), the second-youngest residents, and the lowest percentage married. Besides specializing in education/medicine, these metropolises also have the second-highest LQs for information and arts, entertainment, and recreation, aligning with a substantial presence of the creative class.

The effect of large universities on housing markets is mostly related to universities' employees (besides students living off-campus, since in this article we use LQs of employment regardless of percent students) because such institutions are oftentimes the largest employers in their second-tier MSAs, creating a distinct dominance in otherwise smaller and less diverse economies. Hence, the very high RBIs of this type emphasize the prominence of economic specializations in affecting rent burden. Indeed, Hajrasouliha

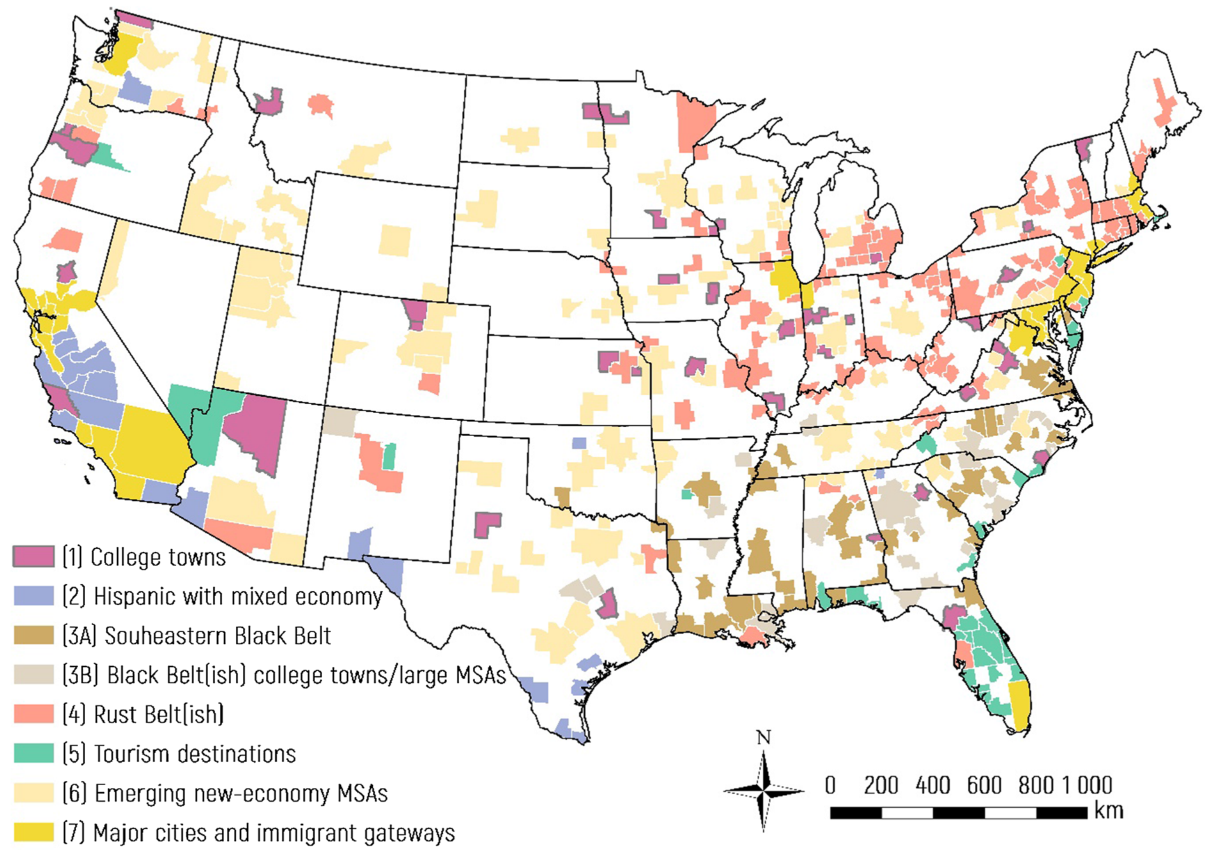

Fig. 2 Typology of the conterminous U.S. MSAs by their rent burden and its potential drivers. Own work based on authors' calculations and statistical analyses

and Hamidi (2017)'s monocentric employment type of MSAs corresponds very well to our Type 1 capturing college towns. This makes sense since in second-tier MSAs, large campuses serve as overarching anchors of employment (i.e., monocentricity in Hajrasouliha and Hamidi's analysis). Finally, while there is little doubt that college towns exhibit higher rent burden, such places also tend to be anti-development. The dominant form of employment there provides a significant job security, so that many of the politically active residents have little to gain and much to lose by consenting to new housing developments (for more on anti-development sentiments toward affordable housing see Monkkonen & Manville, 2019; Tighe, 2010 as well as others in the "Background" section).

Type 2: MSAs with noticeable Hispanic populations and mixed economy

This type demonstrates no pronounced specializations in terms of the six select industries, but has the highest agriculture[1] LQs. Such MSAs exhibit heightened RBIs

[1] After analyzing Type 2 more closely, we decided to calculate agriculture LQs for all MSAs. This was not our initial intent to include such industry, however, because of two major reasons: (i) non-urban nature of agriculture employment; and (ii) a small number of agriculture employees in the U.S. economy which is now dominated by the tertiary, quaternary, and quinary sectors. The means and medians of agriculture LQs for the entire sample are 1.32 and 0.76, whereas these figures for Type 2 MSAs are 4.96 and 5.14, which indicate a very high specialization compared to all U.S. MSAs. Additionally, see Spangler et al. (2020) whose work demonstrates current agricultural patterns in the U.S., especially the role of the California's Central Valley which includes several MSAs of Type 2 (in fact, this valley is the only agricultural area that also has relatively high population densities).

along with the second-highest presence of foreign-born populations and the largest shares of Hispanics, especially along the U.S.-Mexico border. This type has the youngest population by median age and the largest household size, along with higher levels of single parenthood that cumulatively add to households' material hardships including rent burden. Type 2 MSAs also have the highest unemployment rates and the lowest levels of health-insured households. Such MSAs are located along the U.S.-Mexico border and the Central Valley of California, but also comprise several second-tier MSAs with higher percentages of Hispanic populations and accompanying characteristics.

Type 3: Southeastern Black Belt[2] with two subtypes

This is the most localized type which has the fourth-highest RBIs along with the highest percentage of Black populations as well as the extent of single parenthood. Additionally, lower levels of health-insured households and higher poverty, unemployment, and school dropout rates (compared to all MSAs) likely exacerbate rent burden there despite the fact that only a few metropolises in Type 3 can be considered hot/tight housing markets. Interestingly, this type has the largest share of newly-built housing (2010–2019).

There are some rather counterintuitive cases within this type (e.g., Atlanta, GA and Shreveport, LA together) and because of that, we divide it into two subtypes that naturally emerge from the data distance in the k-means generated clusters. Specifically, the distance intervals for the two subtypes are ~ 1.0 (from 0.499 to 1.480 for 3A and from 1.502 to 2.519 for 3B) and there is a significant natural break roughly at 1.5 which separates mostly college towns and major MSAs (also with multiple large universities) in the Southeast from other, more typical Black Belt MSAs. A similar logic for some minor intervention can be found in Mikelbank (2004: 948) along with an elaboration on minimizing the intra-cluster variation and the use natural breaks for such purpose.

Subtype 3B demonstrates some duality in a way that college towns and large MSAs in the Southeast demonstrate quite similar characteristics and thus are grouped together. Despite some outliers in that subtype, most exemplary cases (Table 2) and this subtype in general have heightened rent burden as compared to the entire sample. Subtype 3A also demonstrates higher rent burden, but this is mostly associated with lower incomes and other socioeconomic-status-related issues, and not with attractiveness and hot housing markets which are mostly the case with 3B MSAs.

While both Subtypes 3A and 3B share many similar characteristics that put them together in Type 3 (e.g., higher poverty and unemployment rates, more high school dropouts, a higher incidence of single-parent households with children, and many households without health insurance), what distinguishes them is their economic specializations with 3A exhibiting higher LQs in arts/entertainment (e.g., Biloxi, MS) and manufacturing (e.g., automobile and aerospace industries; see URL1), whereas 3B specializes more in education/medicine (e.g., Atlanta, Charlotte, Durham-Chapel Hill, etc.). In addition, Monroe, LA, hosts headquarters of a significant company—Lumen Technologies—which is its second-largest employer (making its LQ-information the highest, 1.93, within the entire Type 3 comprising 60 MSAs). Monroe is also home to a regional campus within the University of Louisiana System. Because of all these reasons, this second-tier MSA is assigned to Subtype 3B together with major metropolises of Atlanta, Durham-Chapel Hill, etc. This re-classification of Type 3 MSAs eventually puts Shreveport and similar MSAs in Subtype 3A, which aligns better with classic Black Belt metropolises.

Type 4: Rust Belt[3] MSAs and older industrial towns

These metropolises are rather localized, yet a few cases are scattered across the nation. Type 4 demonstrates the second-lowest RBIs, the lowest share of

[2] In this article, we refer to a broader definition of the Black Belt as a region spanning from Virginia into northeast Texas (see maps in Chi et al., 2019; Wimberley, 2010). We do not mean the Black Belt region of Alabama (Sharma, 2016) which is a specific group of counties across the midsection of Alabama with dark soils that became a center for plantation slavery and today have majority African American populations.

[3] The Rust Belt refers to a region stretching from western New York state to Illinois (see map in Thompson & de Beurs, 2018). It is known for significant population declines in many cities within this region and for economic restructuring and deindustrialization since the 1970s. However, the region still has a heightened proportion (compared to the U.S. as a whole) of the workforce employed in manufacturing according to our calculations. Indeed, manufacturing continues to matter to the Rust Belt (Hobor, 2013) despite several decades of urban shrinkage and economic restructuring.

Table 2 Ten representative examples of MSAs for each (sub)type

Type	Primary cities of MSAs
1 (n = 36)	Ames (IA), Ann Arbor (MI), Auburn (AL), Bloomington (IN), Boulder (CO), Corvallis (OR), Ithaca (NY), Lawrence (KS), Lubbock (TX), Muncie (IN)
2 (n = 21)	Brownsville (TX), Corpus Christi (TX), Dalton (GA), Fresno (CA), Laredo (TX), Las Cruces (NM), McAllen (TX), Visalia (CA), Yakima (WA), Yuma (AZ)
3A (n = 37)	*Large*: Birmingham (AL), Columbia (SC), Jacksonville (FL), Memphis (TN), Richmond (VA) *Second-tier*: Columbus (GA), Jackson (TN), Lake Charles (LA), Montgomery (AL), Shreveport (LA)
3B (n = 23)	*Large*: Atlanta (GA), Charlotte (NC), New Orleans (LA) *College towns*: Durham-Chapel Hill (NC), Greenville (NC), Jonesboro (AR), Tallahassee (FL), Tuscaloosa (AL), Valdosta (GA), Waco (TX)
4 (n = 103)	*Large*: Cleveland (OH), Detroit (MI), Pittsburgh (PA), St. Louis (MO) *Second-tier*: Albany (NY), Allentown (PA), Erie (PA), Evansville (IN), Flint (MI), Peoria (IL)
5 (n = 32)	*Inland*: Asheville (NC), Bend (OR), Hot Springs (AR), Santa Fe (NM) *Coastal*: Atlantic City (NJ), Barnstable (MA), Brunswick (GA), Daytona Beach (FL), Myrtle Beach (SC), Palm Bay (FL)
6 (n = 105)	*Large*: Dallas (TX), Denver (CO), Indianapolis (IN), Minneapolis (MN), Nashville (TN) *Second-tier*: Chattanooga (TN), Fargo (ND), Knoxville (TN), Madison (WI), Reno (NV)
7 (n = 23)	Boston (MA), Chicago (IL), Los Angeles (CA), Miami (FL), Philadelphia (PA), San Diego (CA), San Francisco (CA), San Jose (CA), Seattle (WA), Washington (DC)

newly-built housing, but the highest specialization in manufacturing. Said differently, a lack of specialization other than manufacturing attracts employees of specific job profiles, making such MSAs less appealing for current/future residents (also a deterrent for new housing construction, especially given very high sunk costs), and thus rent burden is less of an issue there. We conjecture that manufacturing specialization being negatively associated with rent burden might be the case in some second-tier, classic Rust Belt MSAs with the remnants of Fordist path-dependency.

Type 5: tourist destinations and retirement havens

This type includes noticeably rent-burdened MSAs with the highest LQs for arts, entertainment, and recreation. Type 5 comprises a pronounced stratum of foreign-born, predominantly Hispanic residents, likely catering to tourists and substantial shares of older, retired, and married populations. Type 5 also has the highest percentage of uninsured households and high school dropout rates. Higher rent burden could be because of limited disposable income and lower hassles from renting rather than owning a house.

Type 6: emerging new-economy MSAs

This is a very diverse and the largest group of MSAs scattered throughout the U.S., with the majority of cases west of the Eastern Continental Divide. Type 6 scores the second-highest in manufacturing specialization, followed by information (likely alluding to more innovative, post-Fordist manufacturing found in new-economy MSAs), and has the highest percentage married. RBIs are the lowest of all seven types despite some metropolises exhibiting high rent burden (Denver, CO or Portland, OR) that get overshadowed by numerous but more affordable second-tier MSAs. This type demonstrates the lowest levels of socioeconomic disadvantage compared to all other types. In addition, emerging new-economy metropolises have the second-highest percentage of new housing construction (just a little behind Type 3) that may alleviate rent burden to some extent (as also noted by Durning, 2017).

Type 7: major cities of global importance and immigrant gateways

Such metropolises have the highest RBIs and exhibit extremes in select characteristics. Type 7 metropolises are the largest by both population size and population density, and have the highest percent foreign-born and Hispanic populations. Despite their size and a diverse economic base, this type scores the highest in terms of information LQs. Higher rent burden in these MSAs could be because of their domestic and international appeal (including their diversified industrial structures) to a diverse set of populations. This type is not confined to any geographical region; instead, it is defined by its hot/tight housing markets coupled with significant shares of minorities and foreign-born populations.

Since findings from typologies are often presented as a series of case examples (Ayres & Knafl, 2008), Table 2 provides exemplary cases of select MSAs that might be otherwise difficult to locate in Fig. 2.

Conclusions

In this article, we develop a typology and provide insights for a rent-burden framework (part of developing a firm theory) allowing the identification of holistic categories of metropolitan areas by their similarities/differences in terms of rent burden. While exploratory in nature (i.e., causal relationships are beyond our scope here), this typology specifies metropolises with similar potential drivers of higher/lower rent burden and how they might align closely in terms of other attributing characteristics. As such, this article addresses an issue of social/economic (in)justice of rent burden through a geographical lens—an important step toward creating equitable and socially-just rental policies.

We derive seven distinct types (with one having two subtypes within it) whose rent burden intensities are related to the varying levels of regional economic specializations (manufacturing, information, education/medicine, and arts, entertainment, and recreation), demographics, family structure, and other socioeconomic and built-environment characteristics (see variables in Table 1). Our analysis of identified types implies that rentals tend to be affordable in locations with prior/current specialization in manufacturing since such metropolises offer fewer opportunities and are prone to job losses and prolonged economic distress in the post-industrial era. Simultaneously, metropolises with pronounced specializations in education/medicine, information, and arts, recreation, and entertainment exhibit higher rent burden which may come as a price for employment opportunities that contribute to making such rental markets hot/tight. Interestingly, emerging new-economy metropolises tend to exhibit lower rent burden, likely reflecting the benefits of newer-built housing and diverse economies. This is underscored by relatively low levels of socioeconomic disadvantage reflected in several characteristics (Appendix A) of Type 5 metropolises compared to other types. Our analysis also finds overall mixed relationships between new housing and types, raising doubts about the prevailing notion of rent burden being a manifestation of the housing demand/supply mismatch *only*.

Moreover, our results suggest that university campuses serve as engines for economic growth and have significant impacts on local housing markets and their rent burden. The same applies to metropolises with large shares of workforce employed in information as well as recreation and tourism. However, in contrast to college towns (and the neighborhoods surrounding such campuses in major MSAs), the effect of these specializations is more difficult to precisely localize at the granular scale (i.e., no distinct concentrations like those in the case of college campuses). Thus, building upon our findings, examining rent burden in college towns or resort/gambling cities could be a timely contribution to the housing and rent burden literature.

Another key takeaway of this typology is that rent burden is an almost ubiquitous issue. This is exemplified by Type 2 and Subtype 3A in which metropolises demonstrate relatively high rent burden despite, for the most part, not being rather attractive locations. Heightened rent burden in these types is attributed to lower income potentials, likely stemming from low human capital skills, race/ethnicity, immigration/legal status, education, unemployment, and household structure.

Limitations of this study include the inability to delve deeper into relationships between different variables/proxies because of (i) the specific methodology of PCA and cluster analysis employed here and (ii) a focus of this article on creating and analyzing complex aggregate types of MSAs instead of examining causality between various phenomena (in that case, we would have used the word determinants instead of drivers). Another limitation is that there are likely other omitted drivers of rent burden which are unaddressed in this article. Indeed, although 69% of the explained variance by six principal components is rather high for numerous socioeconomic variables, still 31% of the missing variance may contain important omitted variables and local political phenomena (e.g., opposition to newer developments, especially affordable rentals and particularly in college towns with heightened rent burden).

We understand that select MSAs in certain types may raise questions about the validity of grouping them together. However, we believe that any attempt to manually regroup software-produced types by incorporating (i) personal or common knowledge on some metropolitan areas or (ii) perceptions about those areas, would undermine the validity of the reported results instead of amending them. Typologies are never fully satisfactory as they do not always produce expected and/or neat results. This is a common limitation for this technique coupling PCA and cluster analysis. We also believe that the typology analysis could have produced a somewhat different set of types if the scale of analysis was individual cities. However, given the larger applicability of economic interdependencies between and among cities and other jurisdictions comprising MSAs, as well as the usage of MSAs as a scale of analysis in other typology studies, our attempt to develop seven types using 380 MSAs has produced interesting results and meaningful geographic knowledge.

Finally, our typology analysis theoretically advances the existing knowledge on rent burden by adding the occupation-related dimension to holistically studying rent burden and its potential drivers from a geographic perspective. Our work will help social scientists and policymakers to understand that *rent burden* is not only the housing supply/demand mismatch issue, but also an issue of income stemming from regional economies and local job market characteristics. These relationships have largely been omitted in scholarly work and practice. Hence, it is worthwhile to consider these when developing measures for alleviating rental housing unaffordability in different settings and at various levels, especially at local and state ones.

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Data availability The data are publicly available.

Declarations

Conflict of interest The authors declare no competing interests related to this article.

Ethical statement The authors comply with research and publication ethics. No ethics approval and consent were needed for this research involving no human subjects.

Appendix A

See Table 3.

Table 3 Means and medians of select variables for each (sub)type and all MSAs

		Rent burden index	Population density	Foreign-born, %	Commute, min	No insurance, %	Married, %	Poverty rate	Unemployment r	Median age	†High school	‡Childr. sing. par	LQ manufacturing	LQ arts, recreation	LQ education/med	LQ information	Black, %	Hispanic, %	Household size	††New housing	Population (1,000)
All	med	42.2	186	6.2	23.0	7.9	48.2	13.6	5.3	38.3	3.73	31.6	0.99	0.97	1.03	0.76	6.9	7.3	2.39	4.92	246
	mean	44.0	283	8.1	23.2	8.5	48.4	14.1	5.4	38.4	4.01	31.5	1.09	1.02	1.06	0.78	10.7	13.7	2.43	5.58	730
7	med	**59.6**	**788**	**21.8**	**31.0**	6.4	47.8	10.7	**5.7**	38.1	2.77	26.9	0.85	0.95	0.91	**1.06**	7.3	**26.4**	**2.68**	3.52	**2,796**
	mean	**60.9**	**1,022**	**22.6**	**30.5**	6.9	47.9	10.5	**5.6**	38.0	2.68	26.9	0.84	0.99	0.96	**1.16**	10.6	**26.8**	**2.70**	3.74	**4,053**
6	med	31.7	158	**6.4**	22.0	**8.7**	**51.3**	11.5	4.2	37.0	**3.79**	27.5	**1.05**	0.91	0.96	0.75	4.4	**7.8**	2.38	**6.44**	**250**
	mean	31.8	214	7.2	22.5	**9.0**	**51.5**	11.5	4.3	37.2	**4.02**	27.0	**1.23**	0.93	0.98	**0.80**	5.8	12.2	2.39	**7.10**	678
5	med	**56.5**	**237**	**8.1**	**25.0**	**11.0**	**50.6**	12.5	**5.4**	**47.4**	**4.57**	**32.9**	0.76	**1.37**	0.92	**0.78**	9.0	**11.9**	**2.55**	4.81	221
	mean	**57.9**	**291**	**9.5**	**24.8**	**10.4**	**50.9**	13.1	**5.7**	**47.5**	**5.66**	**32.3**	0.57	**1.46**	0.91	0.76	9.5	**14.0**	**2.56**	**6.05**	437
4	med	40.3	**220**	4.2	23.0	5.5	47.6	**13.9**	**5.4**	**40.5**	**4.08**	**33.9**	**1.35**	0.96	**1.09**	0.76	6.9	4.8	2.21	2.63	199
	mean	41.4	**296**	4.8	22.6	6.0	47.9	14.0	**5.5**	**40.7**	**4.33**	**34.2**	**1.34**	0.96	**1.11**	0.74	7.8	7.5	2.23	2.88	487
3B	med	**44.8**	140	4.1	23.0	**10.3**	44.9	**16.9**	**6.8**	36.4	**4.06**	**38.0**	0.91	0.97	**1.08**	0.68	**34.2**	6.6	**2.51**	**7.30**	229
	mean	**45.5**	191	5.5	23.0	**11.2**	45.2	**17.0**	**6.9**	35.2	**4.25**	**38.0**	1.01	0.99	1.06	0.76	**30.6**	9.3	**2.51**	**7.69**	649
3A	med	**45.2**	186	4.3	**24.0**	**10.4**	46.1	**15.1**	**6.2**	37.6	**4.32**	**37.5**	**1.01**	**0.98**	1.01	0.72	**29.5**	5.5	**2.51**	**6.82**	**386**
	mean	**45.2**	217	4.7	**24.0**	**10.4**	46.0	**15.4**	**6.4**	37.4	**4.33**	**37.5**	1.07	**1.03**	1.03	0.70	**29.4**	6.0	**2.50**	**6.86**	499
3	med	**45.1**	170	4.3	**24.0**	**10.3**	45.7	**15.6**	**6.5**	36.9	**4.21**	**37.6**	**1.01**	0.97	1.02	0.68	**29.6**	6.0	**2.51**	**6.85**	**303**
	mean	**45.3**	207	5.0	**23.7**	**10.7**	45.7	**16.0**	**6.6**	36.5	**4.30**	**37.7**	1.05	1.02	1.04	0.73	**29.9**	7.3	**2.50**	**7.18**	557
2	med	**48.3**	109	**21.2**	22.0	**10.3**	46.5	**17.1**	**6.9**	33.0	**4.20**	**33.8**	0.67	0.91	0.95	0.52	2.6	**58.8**	**3.15**	4.81	**273**
	mean	**50.1**	163	**20.6**	22.6	**13.8**	47.4	**17.6**	**7.6**	33.0	3.98	**33.7**	0.84	0.95	0.99	0.55	2.8	**60.5**	**3.13**	5.63	395
1	med	**58.6**	138	**7.3**	20.0	6.2	44.2	**20.1**	4.3	33.3	1.94	26.9	0.82	**1.08**	**1.35**	**0.84**	4.2	5.7	2.27	**6.46**	167
	mean	**59.6**	161	7.5	20.4	6.9	43.9	**19.8**	4.8	33.7	2.00	27.5	0.88	**1.13**	**1.36**	**0.84**	6.3	8.2	2.27	**6.94**	198

†High school dropout rate; ‡ percent children living with single parents; †† percent housing units built during 2010–2019 in total housing stock

Population density is per sq. mile

For legibility, the rows with medians are italicized and the cells with values above those of the entire sample are bolded

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