A Profile-Based Approach to Indexing Housing Vulnerability in Tucson: A Case Study of Manufactured Housing

Making Action Possible in Southern Arizona (MAP Dashboard)
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Executive Summary

Housing insecurity is the uncertainty felt by individuals and households about the stability, safety, adequacy, or affordability of their home and neighborhood (Raymond et al. 2018, Cox et al. 2019). Households can be insecure for many reasons, from overcrowding and illness to job loss and neighborhood change. This white paper focuses on mobile and manufactured housing (MH), which has unique characteristics that can make its residents more *vulnerable to housing insecurity* than those who live in site-built housing for cultural, historical, and legal reasons. Fortunately, factory-built housing is not inherently vulnerable; indeed, MH is potentially less costly to construct, install and purchase, and more energy efficient than site-built housing (Burch et al. 1993; Baechler & Hadley 2002). MH offers a high quality of life at low cost that allows residents to raise healthy families or "age in place."

To address this "MH gap," we develop a novel approach for (i) identifying populations of MH households most vulnerable to housing insecurity and (ii) mapping these populations to better understand their geographies. To do so, the white paper analyzes census microdata from nearly 2,000 MH households in Pima County. This process revealed two MH households profiles whose constellation of vulnerability factors suggest *they are* more likely to be vulnerable to housing insecurity. These profiles are (i) fixed-income seniors (FIS) and (ii) low-income households living in older homes (LIO). After using qualitative data from interviews with 72 Pima County MH residents and other techniques, to confirm these results, the profiles were converted into MH-specific vulnerability indices and mapped (see Figure 0).

Key findings and contributions:

- The most vulnerable profile groups of MH residents in Pima County / Metro Tucson are Fixed-Income Seniors (FIS) and the Low-Income, Old MH (LIO) households.
- The identification and mapping of these profiles will help policy makers and social service providers better direct their resources to close the MH gap.
- To address the unique characteristics of MH, a method for creating MH-specific vulnerability indices is developed. While in this white paper depth with respect to housing type, and geography are prioritized, the method is applicable to other cities and scales, and all housing types.
- Qualitative methods are combined quantitative analyses (logistic principal components analysis) to select among possible statistical models.
- The most geographically widespread MH vulnerability profile in Tucson is Low-Income Older MH (LIO).
- Vulnerability profiles rarely spatially overlap: FIS and LIO vulnerability profiles only overlap in five census block groups.

Conclusions:
Mobile and manufactured housing is arguably Tucson's most important and largest source of unsubsidized affordable housing. However, it is also the nexus of vulnerabilities that can make its residents housing insecure. This white paper aims to help policy makers and housing advocates to recognize MH's value and importance despite the ways in which it has been marginalized – by creating a tool that distinguishes the MH subpopulations most vulnerable to housing insecurity from the MH population as a whole. Using principal components analysis, we were able to identify MH-specific profiles of vulnerability, and then produce mappable indices corresponding to these profiles. This novel approach achieves two broad goals.

- 1) It avoids reinforcing perceptions of MH as an inherently inferior form of housing, and instead recognizes that MH can be both good and bad housing for highly differentiated populations – like any other housing type. Many vulnerability indices use MH as an indicator of vulnerability – suggesting that factory-built housing is a proxy for vulnerability and/or homogeneously correlated with vulnerability. This elision of the complex relationship between MH and vulnerability highlights some of the limitations of broader, more generalized, vulnerability indices.

- 2) The white paper provides insights that are tailored to specific populations with unique needs. This will allow local policy makers, service providers and researchers, to better serve and understand the needs of vulnerable groups. Given the non-traditional characteristics of MH and the current lack of a widely accepted evaluation tool for housing insecurity, the ability to zero in on specific populations is particularly valuable.

The methods developed in this white paper will allow future researchers to ask questions about how MH vulnerability has changed over time, varies by socioeconomic status and other household characteristics, and use inferential techniques to better determine its causes and the potential effects of policy interventions.

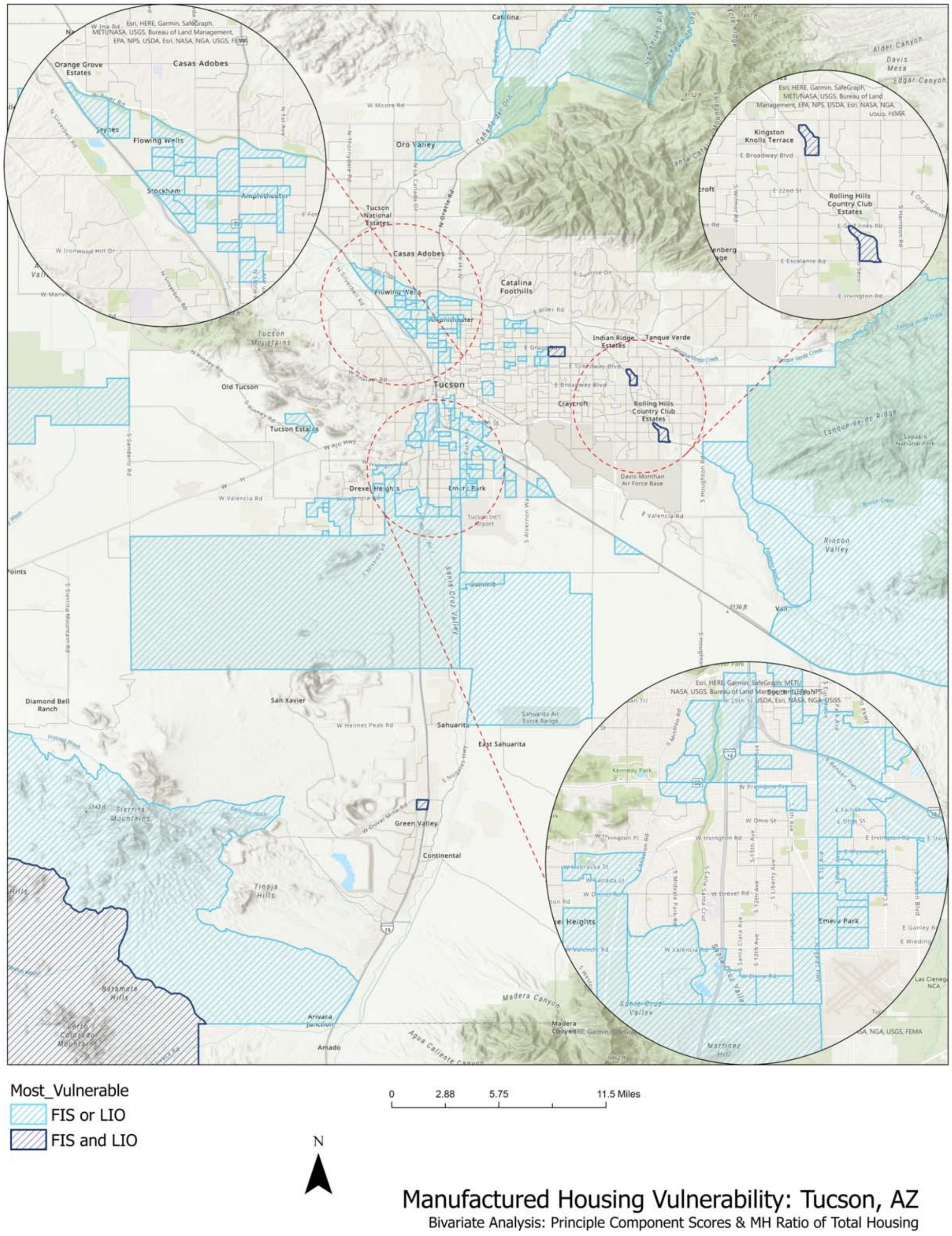

Figure 0: Most Vulnerable Census Block Groups: Map of the most vulnerable MH profile groups and their intersections.[1]

[1] Some block groups that cover vulnerable MH residential areas also cover US National Forest or National Park lands. This is due to their large size. More refined spatial enumeration units would differentiate between these land uses.

Introduction

Housing insecurity is the uncertainty felt by individuals and households about the stability, safety, adequacy, or affordability of their home and neighborhood (Raymond et al. 2018, Cox et al. 2019). Households can be insecure for many reasons, from overcrowding and illness to job loss and neighborhood change. Underlying housing insecurity are myriad factors such as energy cost burden, lack of access to healthy food or employment, inadequate public infrastructure, and high transportation costs, among others. A key source of variation among these conditions of insecurity is housing type[2] (Kain 1968; Bogdon & Can 1997; Shen 2005; Stone 2006; Sampson 2008; Acevedo-Garcia et al. 2016; Desmond & Gershenson 2016; Chetty et al. 2018).

In this white paper we focus on mobile and manufactured housing (MH), which has unique characteristics that can make its residents more economically, environmentally, and socially *vulnerable to housing insecurity* than those who live in site-built housing for cultural, historical, and legal reasons. This focus on MH does not imply that all MH is the same or that lower-cost housing built in a factory is inherently insecure. On the contrary, research has found substantial variation in the quality of life that this widely stigmatized housing type is able to support (Founds 2021). However, the lived reality of MH often falls short of its potential as a source of high-quality, energy efficient affordable housing, creating what we call the "MH gap". To address this heterogeneity, we develop a novel approach for: (i) identifying populations of MH households likely to be experiencing some form of insecurity; and (ii) mapping these populations to better understand their geographies. Information arising from this approach can help policy makers and social service providers better direct their resources.

The white paper is centered on the analysis of census microdata from nearly 2,000 MH households in Pima County.[3] Our analysis found three profiles of MH households whose constellation of vulnerability factors suggest *two* of them are more likely to be experiencing housing insecurity. These profiles are: (i) fixed-income seniors (FIS); (ii) low-income households living in older homes (LIO): and (iii) low-to-moderate income working people living alone (WLA). These profiles and associated populations, while sharing much in common, also have unique

[2] Housing can be broken down by type in a variety of ways. For example, housing could be broken down into multi-unit structures (apartment buildings, and duplexes), townhomes, and detached single-family homes, or according to tenure (rent versus own). As discussed below, MH often fits poorly into these taxonomies.
[3] The census boundaries for the Tucson metropolitical statistical area (MSA) are the same as those of Pima County. Consequently, the terms are both used to refer to the same geography.

financial, social, and environmental vulnerability characteristics and are distributed differently across the city. As a result of these distinctive geographies and vulnerability characteristics, we argue that policies to address vulnerability and housing insecurity among MH households can benefit from metrics tailored to the circumstances and needs of each profile group within the MH resident population; in other words, metrics that do not treat people who live in MH as a homogenous group with a common set of stereotypical characteristics. It is important to highlight populations in need, but also to do so with precision to avoid contributing to negative stereotypes about MH and the people who call it home.

Resident case studies of each vulnerability profile are provided to make the groups they represent more tangible. These case studies are based on real research participants.[4] We use them not just for their individual stories, but as personifications of abstract categories only discernible through statistical techniques (principal components analysis or PCA). Each case study has a degree of correlation with the generalized profiles created by our analysis. These profiles are not a perfect fit for everyone; rather, they are characterized by an individual's relative degree of fit with the categories identified by our analysis. The goal of the analysis is to find general groupings in a population of diverse individuals and households and achieve the best fit possible. Before delving more deeply into how we identified and mapped profile groups (and the benefits of doing so) we provide some historical background about mobile and manufactured housing in Tucson and nationally. In doing so we also explain why studying MH can deepen our understanding of the ways that different forms of vulnerability intersect and cascade to exacerbate housing insecurity.

Background

Manufactured Housing: Nexus of vulnerability and site of hope

In the United States (US) 38 million (one in three) households spend more than one-third of their monthly income on household expenses (Habitat for Humanity 2019), suggesting low-income households are having tremendous difficulty accessing affordable housing options. MH has long been advocated as an affordable housing option and is the largest source of unsubsidized low-cost housing in the United States (Sullivan 2018) and Tucson today. Nationally, MH is home to 22 million people (Revere 2021). In Metro Tucson that number is proportionally higher at 100 thousand, or approximately 10% of the total population.

While playing an important role in affordable housing markets across the country and locally, MH, nevertheless, has unique characteristics that can make its residents more economically,

[4] Research participant identities are confidential. All names used are pseudonyms.

environmentally and socially vulnerable than those who live in site-built housing for cultural, historical and legal reasons. Socially and culturally, MH residents must often contend with housing-based stigma (Kusenbach 2009, Sullivan 2018) as low-quality “trash” housing for “low-class” people. Economically, the classification of most MH as personal property (not real estate) restricts access to lending markets, increases borrowing costs, and exacerbates the impacts of foreclosure and eviction. Environmentally, MH is often more exposed to hazards such as flooding, high winds and wildfire (Rumbach et al. 2020). Older MH is one of the most energy inefficient forms of housing (GAO 2005), making residents vulnerable to extreme heat. Fortunately, there is nothing inherently marginal about factory-built housing; indeed, MH is potentially less costly to construct, install and purchase, and newer MH designs can be more energy efficient than site-built housing (Burch et al. 1993; Baechler & Hadley 2002). Our research on this gap between the potential of MH and the lived reality of many MH residents suggests that well-designed and targeted policy can significantly narrow or even close the “MH gap” (Kear et al. 2019). Understanding the origins and complexity of this gap requires some basic knowledge of the history of MH, which we briefly provide in the next section.

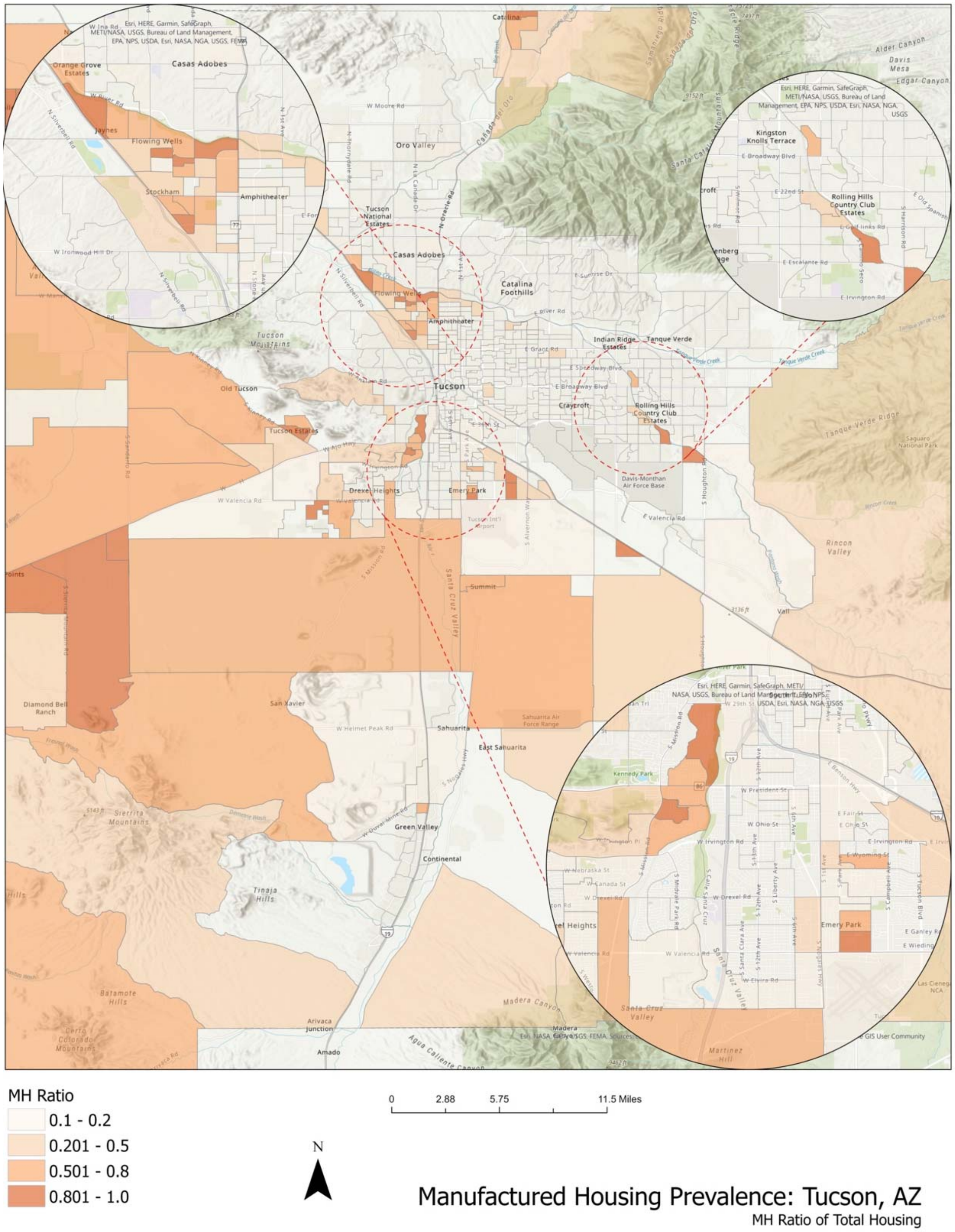

Figure 1. Census block groups (CBGs) in this map show the prevalence of manufactured housing. This map was created by calculating the ratio between MH units and the total units of all housing types in the CBG.

A Brief History of Manufactured Housing

The earliest forms of MH in the US were "trailers" produced by manufacturers in the 1920s as temporary housing intended mostly for vacationers and traveling salespeople (Hart et al. 2002).

As these mobile homes gained popularity, many towns and cities tried to attract tourist dollars by setting up campgrounds catering to middle-class trailer-owning vacationers. Over time, these "trailers" grew in size, making them less mobile but also more suitable for longer-term living. Indeed, the federal government used them to house workers during World War II. While such arrangements were intended to be temporary, shortages of affordable housing for war industry workers and the poor contributed to the proliferation of their longer-term use. They began their stint as permanent housing for construction workers, farmworkers and active military after the war. By the late 1950s, their inhabitants had become more diverse, and "mobile" homes were embraced as starter homes by many families. This change in demographics encouraged design innovations that moved the industry further away from mobility and toward models more closely resembling site-built housing.

This shift away from mobility was accompanied by the growth of "parks", or land-lease communities, wherein landlords rent land to owners of individual MH units. Together these innovations and evolutions transformed MH into the "platypus" of the US housing market — composed of a unique amalgam of characteristics associated with a variety of different housing types. Even today, MH can be multifamily or single-family housing, seasonal or year-round housing, personal property or real estate, rental or owner-occupied, mobile or permanent, and all these mixed together in various permutations. They are also common in informal subdivisions (Durst and Sullivan 2019), Indian Reservations, *colonias,* in the US-Mexico border region, and housing co-operatives, especially in New England. This combination of atypicality and diversity has made MH challenging to regulate and plan for because it fits poorly into extant regulatory, planning and fiscal frameworks based on conventional housing types.

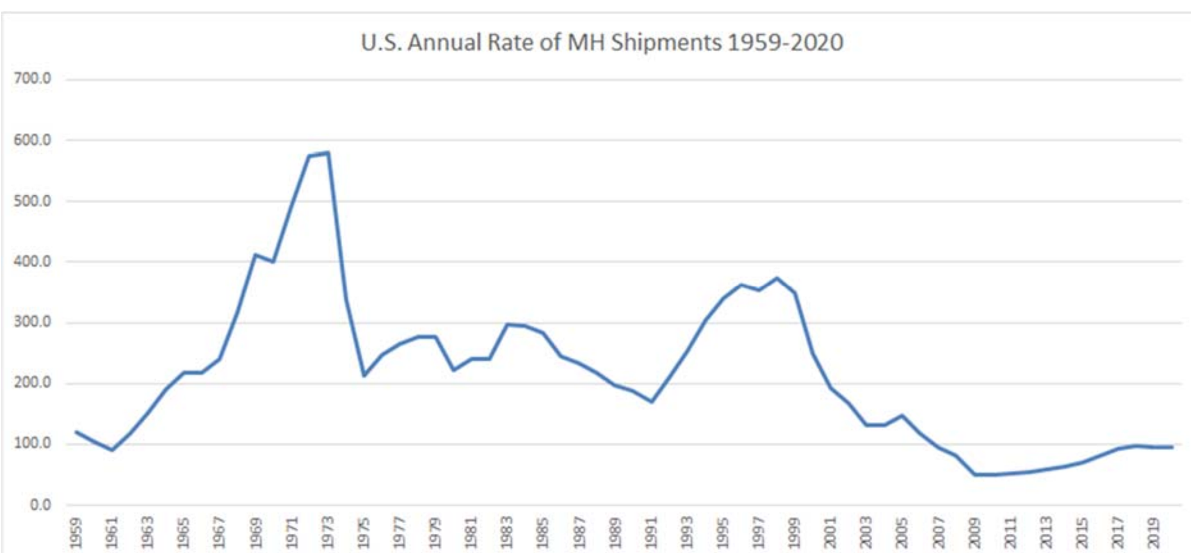

Figure 2. Total MH shipments per year in the United States. While the industry has recovered in the last decade and is growing again, the longer-term trend is one of secular decline, with an all-time peak in the 1970s, and a renaissance in the late 1990s, followed by a crash from which it is still recovering.

As a result, MH's expansion across the US in the 1960s and 1970s (see Figure *2*) was often not well planned, leading to a variety of problems that contributed to negative associations and deep-seated (even unconscious) biases against MH and those who call it home. For instance, in many parts of the country, local regulations did little to prevent overcrowding of trailers in parks or people in trailers. In other areas, MH communities grew faster than local tax codes, leading to concerns that MH "did not pay its own way", creating fiscal burdens for municipalities (Kear et al. 2019). MH is also titled differently than most housing (as personal property / chattel), which has starved the MH market of financing, and prevented MH households from accessing many of the protections available to mortgagees and other homeowners. Today MH in parks is in short supply and high demand, but also mostly tucked away on the urban fringe, and commonly treated as a form of LULU (locally unwanted land use), with few new communities being built and many more under threat of redevelopment or being (re)zoned into noncompliance.

The "HUD Code"

Unlike conventional housing, which must conform to local building codes, MH building standards are coded at the national level. Enacted in 1976, the Manufactured Housing Construction and Safety Standards Act, or the "HUD Code" (in reference to the US Department of Housing and Urban Development (HUD), which administers the law), created a uniform minimum standard for MH, effectively dividing the market into two overarching quality and safety classes – pre- and post-1976. Four decades later, pre-1976 MH still constitutes 35% of Pima County's MH stock (Kear et al. 2019), and its spatial distribution is a map of structural distress. As time has passed this temporal distinction between pre- and post-HUD code MH has become an ever-stronger spatial indicator of various forms of vulnerability. Aging and hazardous materials (e.g. asbestos and formaldehyde), lack of insulation and fire-prone aluminum wiring are some of the reasons that the estimated 17,000 pre-1976 "mobile homes" in Pima County persist as present-day markers of social and environmental vulnerability. But their enduring presence is also an artifact of the past growth of MH in Pima County and across the country. The present geography of MH distress, and social vulnerability is deeply imbricated with the geography of the late 1960s and early 1970s when MH placements boomed across the county and country.

While there is much more to the history of MH than the basics we have shared here, the most important point of this history (and the point of departure for the analysis to come) is that MH is not like other housing types. MH's differential treatment in law and policy throughout its history has fostered forms of stigma and prejudice, as well as patterns of vulnerability, which are not well captured by standard metrics and methods for measuring and mapping social and environment vulnerability. The underlying drivers of MH vulnerability, while not wholly unique, are peculiar enough to suggest that a more tailored approach to the identification, measurement and mapping of vulnerability might be more accurate and produce better insights for policymakers and social service providers to target assistance and other efforts. In the process of developing an MH-specific mappable index of vulnerability, this paper also pilots novel approaches for the development of social vulnerability indices. To contextualize these innovations, in the next section we provide a brief review of the existing literature on vulnerability and resilience, and efforts to measure them.

Vulnerability and Resilience

While the academic literature on vulnerability is sprawling, and includes many definitions and metrics, recent work on vulnerability has focused on the complex interdependence between humans and their environment (Cutter et al. 2003; Adger 2006; Bakkensen et al. 2017). Within this context we can broadly define vulnerability as the susceptibility of an individual or household to economic, social, or environmental shocks and stressors (Adger 2006). Shocks are unexpected and acute adverse events (a flood or job loss), while stressors are conceptualized as chronic weakening disruptions (rising temperatures, or inflation) (OECD 2014; Choularton et al. 2015). The concept of resilience, by contrast, captures the ability to bounce back or recover from shocks and stressors, or the "capacity for adaptation to emerging circumstances" (Adger 2006). Since vulnerability to shocks and stressors is in part a function of adaptive capacity, vulnerability and resilience are concepts that contrast, but also in some sense contain each other. This means that understanding one necessarily entails some understanding of the other.

Contemporary vulnerability research approaches the phenomenon from two perspectives: vulnerability *to* hazards,[5] and vulnerability *due to* socio-economic status, among other potential factors. Since the late twentieth century, researchers have brought these approaches together to more completely consider relations among hazards, and systemic and structural inequalities and how different sources of vulnerability intersect, compound and cascade. There has also been a methodological shift towards quantitative measures of vulnerability. Such assessments aim to capture the nuance of these relationships and demonstrate changes across space and time (Tate 2012). Given the wide variety of contexts in which vulnerability is experienced, multiple approaches have emerged to quantify vulnerability. A common method among scholars is generating index variables, or a composite variable that represents multiple dimensions of vulnerability. Cutter et al. (2000; 2003) have been influential in their theorization of social vulnerability as a function of (i) lack of access to resources, information, and knowledge, (ii) limited access to political power and representation, (iii) weak buildings or infrastructure and

[5] We understand the term *hazard* broadly to include all things causing harm or damage to humans, property, or the environment with focus on the impacts on households and individuals.

lifelines (e.g., evacuation routes), (iv) level of social capital or connectedness in social networks, (v) individual or group beliefs and customs, and (vi) individual physical or mental illness or frailty (adapted from Cutter et al. 2000; 2003). However, there is no tidy agreement about what indicators should be used to represent these dimensions of social vulnerability (or about the dimensions themselves), and several frameworks and indices exist. Furthermore, there is also no standardized analytical method for constructing a concise expression of vulnerability from the vast selection of available and imbricated indicators. Nor is there an index uniquely formatted for evaluating MH vulnerability.

Over the last two decades, quantitative vulnerability assessment methods have expanded to include several techniques, most notably *deductive*, *inductive*, and *hierarchical* approaches (Tate 2012). Deductive approaches aggregate several theory-based variables into a normalized vulnerability score, while inductive approaches rely on computational models to identify unobserved patterns in the data and sort variables into fewer subcategories of vulnerability. Hierarchical methods are somewhat in between, as the researcher manually reduces their variables by sorting them into subcategories based on theoretical background (Tate 2012). Our own approach blends elements from each method, first employing the deductive approach described in our 2019 white paper, where we selected dimensions of vulnerability based on a literature review. Following this, we combined inductive and hierarchical approaches for this white paper by using a subset of census variables in a PCA based on emergent themes from qualitative interviews and surveys across Pima County.

Existing Indices

The most commonly used measure of social vulnerability is the Social Vulnerability Index (SoVI) (Bakkensen et al. 2017; Spielman et al. 2020). This inductive method is based on the earlier deductive *hazards-of-place framework*, which describes vulnerability as an outcome of spatially dependent risk and mitigation factors (Cutter and Solecki 1989). Cutter et al. (2003) refine a large dataset of 85 variables down to a standardized set of 11 variables with the most explanatory power.

Empirical validations of vulnerability indices show that overarching measures like the SoVI, and other indices, can lead to a less precise evaluation of vulnerability among subpopulations (Bakkensen et al. 2017; Spielman et al. 2020). While instruments such as the SoVI provide a helpful preliminary understanding, distinguishing among types of vulnerability better positions local institutions with varying roles and interests to make actionable steps towards vulnerability reduction. Bakkensen et al. (2017) suggest computing specialized scores using relevant components of existing indices. Spielman et al. (2020) advise modifying indices to focus on specific hazards and locations. Flanagan et al. (2011) build upon the SoVI by creating a social vulnerability index specific to disaster management. Their Social Vulnerability Index (SVI) is intended for use as a tool for allocating resources in times of disaster, when such decisions are made more complex by urgency. Using a hierarchical approach, the Social Vulnerability Index (SVI) selects categories associated with vulnerability based on "disaster theory," which aims to improve resiliency and preparedness for natural disasters (socio-economic status, household composition and disability, minority status and language, and housing time and transportation) and then selects census variables to represent each category for a total of 15 variables. The authors then create a cumulative percentile ranking to demonstrate levels of vulnerability within a given census tract. This vulnerability score of a population at the tract level can inform specialized mitigation and response efforts in the event of a natural disaster.

Similar concerns about overarching measures have motivated the creation of housing-specific indices. For instance, Bates (2013) generates a composite variable for vulnerability to housing displacement as part of a multi-pronged analysis of rising housing costs and gentrification in Portland, Oregon. The index aggregates four demographic factors (tenure status, educational attainment, income, and race/ethnicity) into normalized scores. This index has since been applied with region-specific modifications to Austin, Texas; Washington, D.C. (Way et al. 2018); and Tucson, Arizona (Kim 2020). Murphy and Scott (2014) identify six categories of indicators to capture housing vulnerability: employment, income/finances, mortgages, the housing market, stress/support, and life satisfaction. Their approach is tailored to a specific geographic (rural Ireland) and financial (the shocks of the Great Recession and government austerity measures) context.

These context-specific approaches imply that efforts to measure and index vulnerability can be adapted to: (i) the form of vulnerability being studied, (ii) the location, and/or (iii) a specific population in order to reveal deeper insights. This sensitivity to context is also consistent with the literature's broad understanding of vulnerability as a multidimensional and highly contingent phenomenon. In other words, vulnerability is contingent on household and personal characteristics, politics, local and regional environments and economies, as well as a wide range of additional possible factors. However, equal attention cannot be paid to all factors and contingencies. As with most social science research, tradeoffs must be made in vulnerability research between depth and breadth. Research to identify, measure and map vulnerability, whether implicitly or explicitly, must make judgments about when to go deep, and when to prioritize the production of insights generalizable across larger populations and geographies. For this white paper, we have opted for depth with respect to housing type, focusing on MH, and depth with regard to geography, by focusing on Tucson. Notwithstanding these priorities, the method we use is applicable to other cities and scales, and all housing types.

Methods

How to measure vulnerability in a manner sensitive to housing type and location

There is nothing inherently hazardous about factory-built housing. For many, MH offers a high quality of life at low cost that allows residents to raise healthy families or "age in place." There is a large gap (Kear et al. 2019) between the most vulnerable (Reid et al. 2009) and most resilient MH households. This MH gap is manifested in a variety of ways, from substandard conditions to fraught landlord-tenant relationships and evictions, which vary from place to place. This place-based variability, combined with a lack of consensus about how to measure vulnerability and housing insecurity (Bogdon & Can 1997; Stone 2006), impedes the development of widely applicable models (Kim et al. 2017) of MH vulnerability. Further, the particularities of place, such as the prevalence of pre-1976 MH units in Tucson, complicate efforts to construct universal measures of housing insecurity that retain nuance across different urban geographies.

To address these concerns, we blend the two major strands of vulnerability research, focusing on the aspects of vulnerability due to socio-economic status that, in turn, influence susceptibility to hazards. We have taken a number of steps to devise a broadly applicable method that is attentive to the particularities of Tucson and MH, including (i) narrowing our scope to a single housing type, and (ii) utilizing a research design sensitive to local geography. Specifically, we created a dataset of nearly 2,000 MH households living in Pima County from a census public use microdata sample (PUMS). The challenge remains of how to avoid painting this already-stigmatized housing type and resident population with too broad a brush. How do we create an index that filters out resilient households and the households who live on the vulnerable side of the MH gap? To respond to this challenge, we created a model of vulnerability to housing insecurity based on specific subpopulations of MH residents that we identified using a logistic principal components analysis (LPCA), a novel version of principal component analysis (PCA) that expands upon the original by allowing the use of categorical data.[6] By applying a LPCA to our dataset of 2,000 MH households, we identified profiles of groups within the MH population whose characteristics are highly correlated with indicators of vulnerability. To help select among the various models suggested by LPCA, and to validate our selected model of MH vulnerability, we conducted confirmatory analysis using both factor analysis, cluster analysis and qualitative interview data (Kear et al. in prep).

[6] We shall use the terms LPCA and PCA interchangeably throughout the paper, as LPCA is a variant of PCA.

Exploring Tucson's MH Gap: Research design

The methods used in this paper are supported by our earlier efforts to map MH vulnerability in Tucson (see Kear et al. 2019). Previously, to explore the relationship between MH and vulnerability, we identified six dimensions of vulnerability – income and poverty, employment, age, building age, health, and education – and then mapped proxy variables for each dimension in relation to the prevalence of MH at the census block group (CBG) level. To graphically represent the spatial relationship between vulnerability and MH in Pima County, we created a series of bivariate maps, which when layered together allowed us to rank CBGs according to vulnerability and identify the most vulnerable among them.

We have built on this approach to identify important determinants of vulnerability for MH residents in Pima Country. We employed a mixed methods approach where the use of qualitative information from surveys and interviews informed our approach to measure, map, and weight a vulnerability index. Our team used the MH-vulnerability maps from Kear et al. (2019) to inform a sampling strategy for surveys and interviews with MH residents across the city. Over the course of eight months in 2019 and early 2020, our team hosted a workshop with MH practitioners and social service providers, carried out interviews with 72 MH residents, and surveyed 108 more. These interviews and surveys, which focused on social, environmental, and financial vulnerability as well as resident quality of life, revealed phenomena unique to MH that purely quantitative analyses could not.[7] This interview and survey data deepened our understanding of particular characteristics of MH vulnerability in Tucson that could not be gleaned from the exploratory map series of our 2019 white paper. We used this qualitative interview and survey data to inform the quantitative analysis in this white paper.

After using qualitative data analysis (QDA) software to review interview transcripts, we created and assigned descriptive "codes" to sections of the transcript related to social, financial, and environmental vulnerability. These codes were then organized into themes and analyzed for their frequency of occurrence. The most prevalent themes (see Figure *3*) served as a basis for the selection of census variables to be used in the MH vulnerability index developed for this white paper. More specifically, we created a structured compendium of codes with description, and then assigned census microdata variables to each theme. In other words, census variables were treated as proxies for relations of vulnerability revealed in resident interviews.

[7] This research was carried out with the approval of, and in compliance with, the University of Arizona's Institutional Review Board (IRB) and all applicable university policies governing human subjects research.

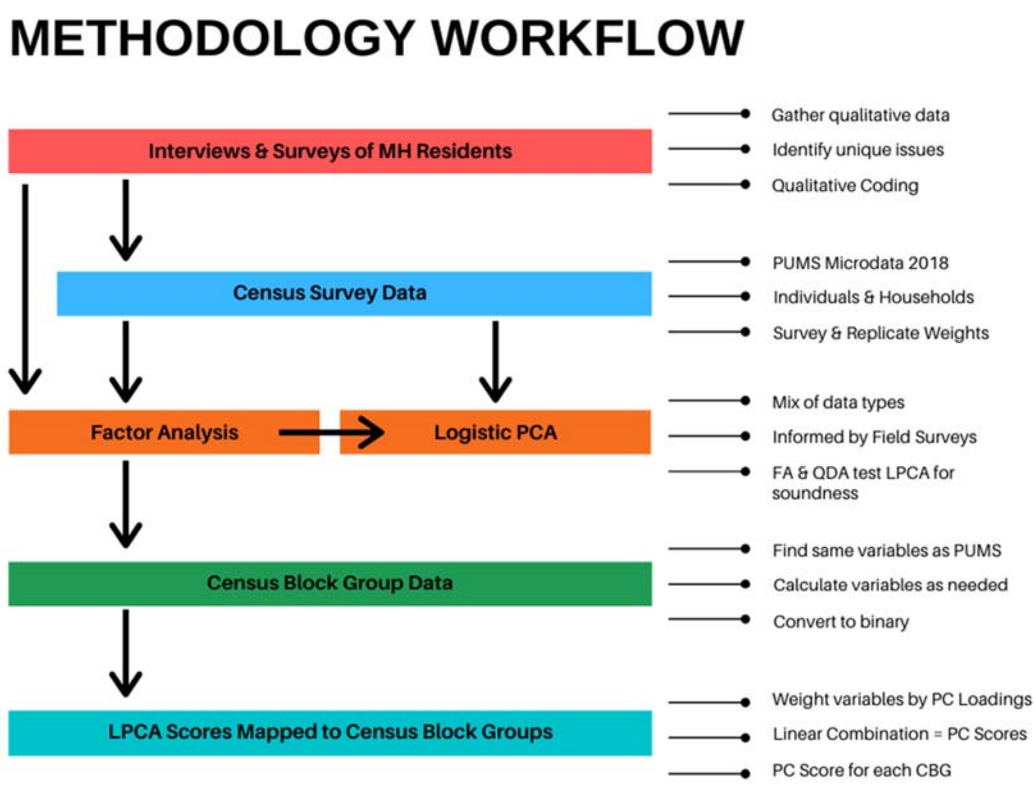

Figure 3. Methodology Workflow. A schematic representation of how we selected our data, analyzed it, tested its validity, transformed results into mappable scores, and the indices of vulnerability corresponding to different profiles of MH vulnerability identified through PCA.

Data

Our analysis of MH vulnerability employs multiple data sources. Our primary statistical data source is the Census Bureau's American Community Survey (ACS) Public Use Microdata Sample (PUMS) for the year 2018. The PUMS data consist of two sets for individuals and households. The two PUMS data sets are designed to be merged to provide our study with information for individuals regarding personal and housing characteristics. Each person is made anonymous through the use of a serial number, rendering individuals identifiable only to the Census Bureau. The LPCA analysis utilizes R and R Studio, and the `logisticPCA` R package, which provides a novel variant of the traditional PCA.[8] Informed by our QDA, we selected microdata

[8] The R language and statistical computing environment is managed by https://www.r-project.org/ . See https://www.rstudio.com/ for information on R Studio. See https://rdrr.io/cran/logisticPCA/f/vignettes/logisticPCA.Rmd for information about R package.

variables for LPCA analysis (see below for more detail on our LPCA) from a set of commonly used variables related to vulnerability (see Table *A1 in the Appendix* for a complete list). The spatial scale of the data, roughly equivalent to the county level (which is the same as the Tucson MSA), also permits the safeguarding of individual privacy.[9]

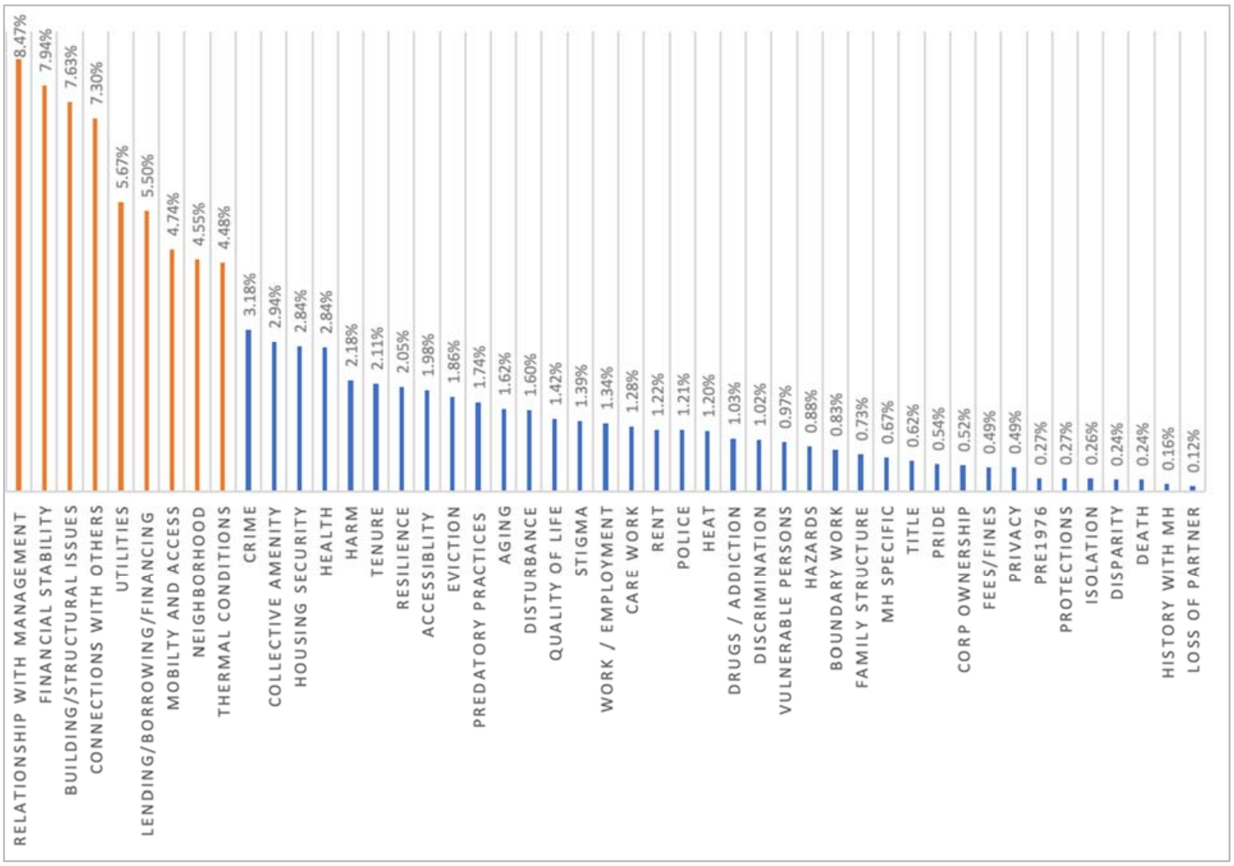

Figure 4. Most prevalent themes of qualitative data analysis. The content of interview transcripts with MH residents was analyzed to identify themes related to environmental, social and financial vulnerability. The chart displays the frequency with which themes occurred in interview transcripts. The most prominent themes are presented in orange. Percentages refer to proportion of all code usages associated with code themes (e.g. 8.5% of code of all code usages were related to the "relationship with management" theme).

Analysis

Logistic Principal Component Analysis

The primary tool used to analyze the microdata variables selected by QDA is principal component analysis. PCA is a statistical technique for determining what set of variables, and loadings on those variables, best capture variation of a latent feature of a population. We use PCA to identify

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[9] Survey weights for individuals and households were applied to selected variables. Replicate weights were used to calculate margin of error on the Pima County PUMS sample variables chosen for the study. We address null values by using the MICE data imputation package in R.

the set of variables, and appropriate relative weightings associated with a latent variable which is consistent with our understanding of MH vulnerability. We use the PCA approach because it provides an objective statistical basis for determining variable weights that can be applied in our MH vulnerability index. In more technical terms, PCA reduces the dimensionality in a set of variables. These correlated variables are individual aspects of the underlying multidimensional process or latent signal. PCA discards a portion of the noise in a dataset, better revealing signal in the data, while also reducing the number of variables. PCA combines those correlated variables within vector space to isolate a latent variable (Bartholomew 2010).[10] For us, that latent variable is the vulnerability of a subset of Tucson's MH population.

A challenge we faced in using PCA, however, is that a substantial number of our selected microdata variables are categorical rather than continuous. Traditional PCA techniques are not applicable to categorical data. There is a range of potential solutions to this problem. One solution is factor analysis with polychoric correlations; unfortunately, our sample size was insufficient to use this technique. Instead, we converted selected variables to binary format (e.g., income above or below a certain threshold were signed a 1 and 0 respectively) and analyzed them using the novel logistical PCA method (LPCA). LPCA applies a "log of the odds" approach to binary data distribution, which produces a probability value for the variable being tested.[11] The result of PCA is a set of composite variables, known as *principal components* or *components*, based on their respective loadings/weightings. This allowed us to select only the most salient variables from the first three principal components of the LPCA for our MH index, as together they accounted for approximately 65% of total variation.[12] Low-income living in old MH (LIO), Fixed-Income Seniors (FIS), and Working Live Alone (WLA) – based on the variables that loaded most highly on each component. For the LPCA method, the criteria for choosing the right model and number of components varies from PCA. See the appendix for cumulative deviance explained.

Discretion and subjectivity influence the application of PCA, especially when it comes to the selection of the "best" model from among the set of possible models suggested by the PCA. Here, confirmatory work must be done. We describe below how we used cluster analysis, QDA and factor analysis to validate our selected model of MH vulnerability to housing insecurity.

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[10] In this format the correlated variables are now in an orthogonal format and thus better suited for the assumptions of ordinary least squares regression (Massey 1965).

[11] One notable distinction of LPCA is that the loadings for the chosen number of components are jointly determined, and therefore not in order of variance, which is referred to as deviance in LPCA. Therefore, each additional component contributes an additional marginal percentage of total deviance.

[12] The technical measure of variability for maximum likelihood estimation of LPCA is called *deviance.*

Confirmatory Analysis: How we selected our components

A K-means clustering analysis was used to evaluate the presence and optimal number of clusters (i.e., groupings of the data values) within the LPCA component scores.[13] The test yielded 3 discernible clusters. The K-means test confirmed the appropriate number of MH profiles, supporting our LPCA results.

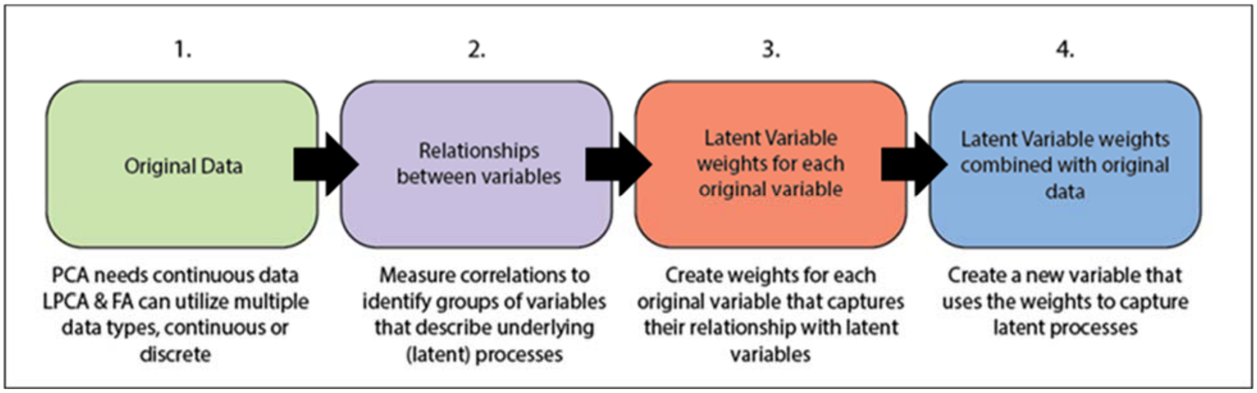


Figure 5. Schematic representation of Principal Component Analysis process & workflow

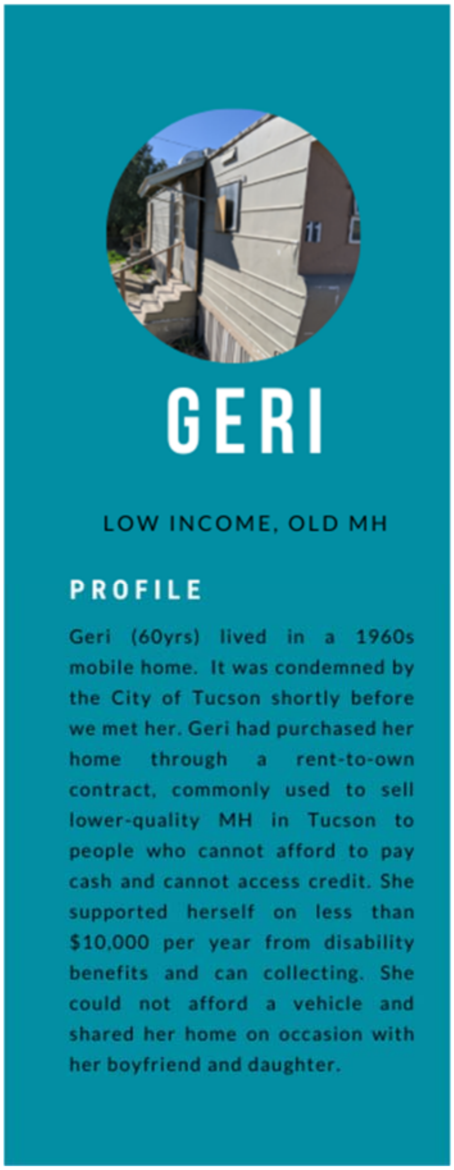
To further validate our LPCA findings, we performed a factor analytical technique specifically designed for the simultaneous analysis of categorical and continuous variables, which also supports our LPCA results.

Results

Our LPCA results and confirmatory analysis suggest that there are at least 3 distinct and dominant profiles of MH households in Tucson. Variable loadings suggest some level of potential vulnerability among two of these profile groups. The three MH profiles are: Low-Income Living in Old MH (LIO),[14] Fixed-Income Seniors (FIS), and Working Living Alone (WLA). Each profile corresponds to a component (AKA composite variable, or principal component), associated with a subpopulation of MH residents and households. We named each MH profile based on the variables in our PCA analysis with which the component was most highly correlated (i.e., based on the most heavily weighted/loaded variables within the component). We describe our results for each profile in turn with summary data and data visualizations provided in Table *1.*

[13] The method compares a "within-cluster sum of squares," (WSS) or squared variance which measures the variance within a cluster, to a "between-cluster sum of squares," (BSS) and seeks to minimize the WSS while maximizing the BSS, repeatedly sorting through the data to find the best fit – the lowest WSS combined with the highest BSS.

[14] Note that the names used in the household profiles are pseudonyms. The identities of all participants in our research confidential.

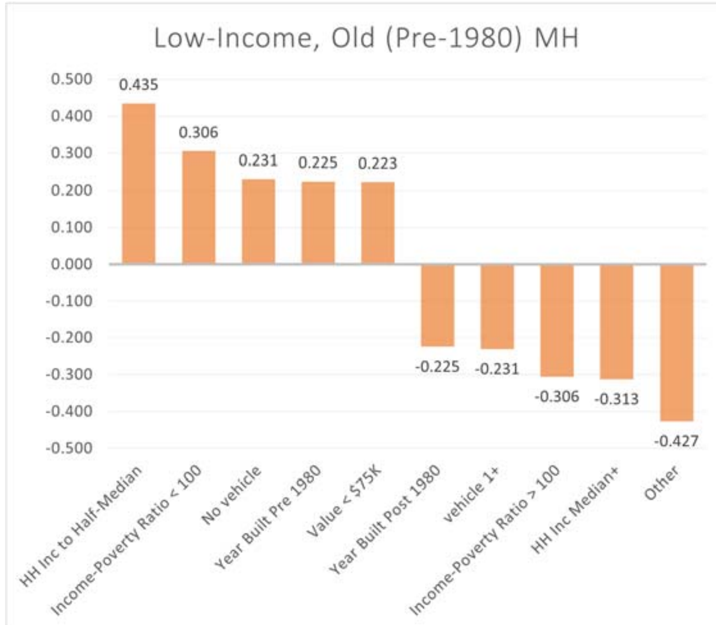


Low Income, Old MH

The MH vulnerability profile identified with the greatest confidence by our LPCA analysis is Low Income Old MH (LIO). The variables of this component had the highest loadings and the absolute sum of the loadings for the variables associated with this profile were the highest among the three profiles identified (see Table *1*). The variables that had the highest loadings for LIO were related to low income and wealth, including: “household income equal to or less than half of median income”, “income-to-poverty ratio less than 100”, and “home value less than $75,000”. LIO also had high loadings for older housing (“pre-1980”), and lack of mobility (“no vehicle”). These variables, beyond suggesting a name for a hidden population, also imply vulnerability. The strength of the loadings on these variables are also corroborated by other sources. We know, for instance, from research on financial capability and environmental justice that low-income groups are less able to manage shocks (Morduch and Schneider 2017) and are disproportionately and adversely affected by environmental hazards.[15]

[15] The closest proxy for pre-1976 MH in our census microdata set was pre-1980.

This corroboration is an essential part of our analysis. While PCA is able to identify populations well characterized by their potential vulnerability, it is important to note that PCA only provides models and sets of correlations. Selecting the “correct” model pertinent to the phenomenon under investigation requires triangulation with a variety of sources. In our case, we rely on extant literature, qualitative interview and survey data and confirmatory factor analysis (see discussion of K-means and FA above). PCA is best used as a part of a multi-pronged, iterative research design that incorporates existing theory and qualitative data.



The case of the LIO profile also illustrates the limits of PCA. PCA does an excellent job of capturing variation in a dataset, but it does not explain how that variation is produced. In other words, high and low loadings on particular variables can help us identify vulnerable groups, but those loadings do not account for the vulnerability of that group. For example, existing literature and research suggests that utility cost burdens are a source of vulnerability for residents of older MH, but electricity cost and gas cost variables had very low loadings for the LIO profile. This only means that these costs do not help us differentiate this profile group from others. Just because there is not much variation in these costs across groups of MH residents does not mean that these costs are unimportant for understanding MH vulnerability. Limits such as these should always be borne in mind when interpreting our results, and PCA analyses, more generally.

KAREN

FIXED-INCOME SENIOR

PROFILE

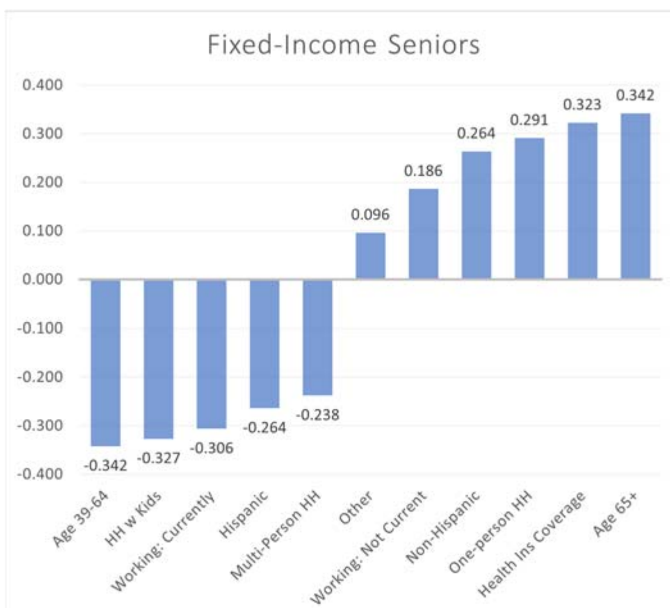
Karen (75) was in the process of being evicted over a billing dispute with her landlord when we interviewed her. She had tried living with her daughter's family prior to moving to her current home, but that did not workout. Her mobile, at a less than $500 per month, was just about the only housing option she could afford on her monthly social security check of $1,000.

Fixed-Income Seniors

The second MH profile identified by our LPCA analysis is Fixed-Income Seniors (FIS). The most salient or influential characteristics of FIS are highlighted in Figure *8* and Figure *9*, as well as Table *1.* Principal component loadings. The variables that loaded most strongly for FIS were related to age ("age 65+"), labor-force status (e.g., "working: not current"), household size and composition ("lives alone" and "households with kids", the latter a negative loading), access to healthcare and ethnicity.

The case for FIS as a profile of vulnerability is less obvious than for LIO. Many of the traditional indicators of vulnerability (e.g., income) do not load as heavily for FIS. We decided to include FIS because older adults are vulnerable in unique ways. Though FIS have access to Medicare and Social Security to help them cope with many shocks and stressors, for many it is not enough. They are also more at risk of social isolation and loneliness (Burris 2021), and other health vulnerabilities, from COVID-19 to extreme heat. Our interviews with MH residents also revealed many older adults in MH facing challenges (see Karen's profile).

We also spoke to several 65-and-older households concerned about "living beyond their savings", suggesting increased financial vulnerability even among moderate income households living on fixed incomes from social security, pensions, and other savings. Moreover, the social service and public health needs of older adults can be distinct from younger populations. Accordingly, an MH index specific to FIS may be of help to service providers and policy makers



concerned with aging populations.

Figure 6. Breakdown of Contributions to Principal Component 2. The data suggest that Fixed-Income Seniors (FIS) are distinct among MH households in terms of age, health insurance coverage, and being out of the labor force.

Working Living Alone

The LPCA identified a third group, which we term Working Living Alone (WLA). While we are confident that WLA is a meaningful subgroup of Tucson's MH population, we are less certain it represents a profile of vulnerability.

WLA's highest loadings were for employment and household-size variables, which together suggest employed people who live alone. On their own, these variable loadings do not suggest an obvious profile of vulnerability; indeed, there is good reason to believe an employed person without dependents might be more resilient and secure than the average household.

However, there are other aspects of this component that are either concerning or ambiguous. For this reason, we are agnostic about the vulnerability of WLA, and believe there is need for further research on this profile. There are two main reasons not to rule out WLA as a profile in vulnerability. First, living alone can be a source of vulnerability in itself. Second, and more importantly, our analysis suggests relatively low levels of health insurance for this profile. This comports with Barnett and Vornovitsky's (2015) findings that unrelated individuals and people living in unrelated subfamilies had lower rates of health insurance coverage than people living in families. Moreover, despite positive correlations for employment, income- and poverty-related variable loadings were low and/or ambiguous for this profile. For example, the variable "income to half median", a low-income variable, had a very low positive loading, while "income-poverty ratio<100", another low-income variable, had a small negative loading. These opposite loadings on similar variables muddies interpretation.

WLA's somewhat confounding combination of positive employment, ambiguous income and negative health insurance loadings raises concerns about household precarity and perhaps connections to unstable contract or gig work, or perhaps self-employment. However, these are connections that cannot be made solely based on LPCA, and, unfortunately, we have very limited data on any individuals that fit this profile through which to gain deeper insight (only one interviewee fit this profile). Here, then, our LPCA has helpfully identified a salient group missed by previous research, along with a new set of research questions for future qualitative investigation.

Mapping Component Scores and The MH Vulnerability Index

LPCA is helpful at identifying profiles but is hard for practitioners to apply to policies and planning goals. Maps can aid in the process by helping us visualize phenomena and see spatial patterns—such as concentration or dispersal—in the profiles of vulnerability we have created. Those spatial patterns themselves have major implications in the lives of the individuals represented by our analysis. Each CBG has a unique combination of the characteristics under analysis in this study, and therefore, unique scores of those composite profiles of vulnerability. Component scores help us identify the strength of the generalized profile of vulnerability identified by a principal component, and those scores are unique to each CBG. Component scores give us a sense of how well each CBG fits the profiles we have established, or how strong each profile is in each CBG.

After we identified and validated the MH vulnerability groups, our next step was to convert these groups into indices and a spatial visualization. This involved converting component loadings, created through an analysis of county- (PUMS) level data, into three indices, each representing a different MH profile, that can be mapped at the CBG level. To do so, we introduce a novel approach for mapping profile (component) scores to CBGs from PUMS microdata. Weights for each variable established by LPCA were applied to corresponding CBG variables as part of a linear combination that created scores for each vulnerability profile (or component, i.e., FIS and LIO) at the CBG level.

To find the most vulnerable CBGs, component scores were mapped in a bivariate relationship with MH prevalence (ratio of MH to all housing) at the CBG level. That relationship was then measured for statistical significance. Bivariate maps (Figure *8* and *Figure* 9) for FIS and LIO were then created to reveal each CBG's profile scores (i.e. component scores for FIS, and LIO), its level of MH concentration, and the intersection of these two phenomena: vulnerability profiles and MH. Then, we created a composite map of the "most vulnerable" locations to find CBGs with high component scores and statistically significant prevalence of MH. These maps were comprised of the high component scores (e.g., for FIS or LIO), consisting of the top third of the distribution of each component/profile, and the presence of MH, measured as the ratio of MH units to all housing units. CBGs where high profile scores for both FIS and LIO are marked with dark blue hash lines; CBGs with high scores for only one profile (FIS or LIO) are marked with light-blue hash lines (Figure *10*).

Principal Component Loadings

Variable Names	Fixed-Income Seniors PC 1	Low-Income, Old (Pre-1980) MH PC 2	Working Low-Income Singles PC 3
HH Income to Half-Median	0.070	0.435	0.006
Income-Poverty Ratio < 100	−0.068	0.306	−0.117
No vehicle	0.036	0.231	0.024
Built Before 1980	−0.030	0.225	0.032
Value < $75K	−0.015	0.223	0.058
Hispanic	−0.264	0.182	−0.134
One-person Household	0.291	0.120	0.357
Age 39-64	−0.342	0.100	0.198
Currently Employed	−0.306	−0.113	0.359
Weekly Workforce Hours ≥ 20	−0.152	−0.136	0.228
Educational Attainment: Higher Ed.	−0.040	0.064	−0.025
Home on ≤ 1 Acres	0.075	0.046	−0.044
Renter Occupied	−0.042	0.046	0.027
Not Employed	0.186	0.038	−0.221
Electricity Cost	0.038	0.032	0.030
No Running Water	0.000	0.021	0.068
Gas Cost	0.013	0.004	0.017
Non-White	−0.025	−0.017	0.059
Migration: Stayers	0.031	−0.018	−0.048
White	0.062	−0.020	−0.013
Home on ≥ 1 Acres	−0.075	−0.046	0.044
Household with Children	−0.327	−0.079	−0.377
Health Insurance Coverage	0.323	−0.084	−0.291
Multi-Person HH	−0.238	−0.097	−0.313
Age ≥ 65 years	0.342	−0.100	−0.198
Weekly Workforce Hours ≤ 20	0.152	0.136	−0.228
Non-Hispanic	0.264	−0.182	0.134
HH Inc Half to Median	0.001	−0.184	0.008
Value > $75K	0.010	−0.190	−0.041
Structure built after 1980	0.030	−0.225	−0.032
Number of vehicles ≥ 1	−0.036	−0.231	−0.024
Income-Poverty ratio > 100	0.068	−0.306	0.117
Household income ≥ median	−0.046	−0.313	0.040

−0.38 0.44

Table 1. Principal component loadings.

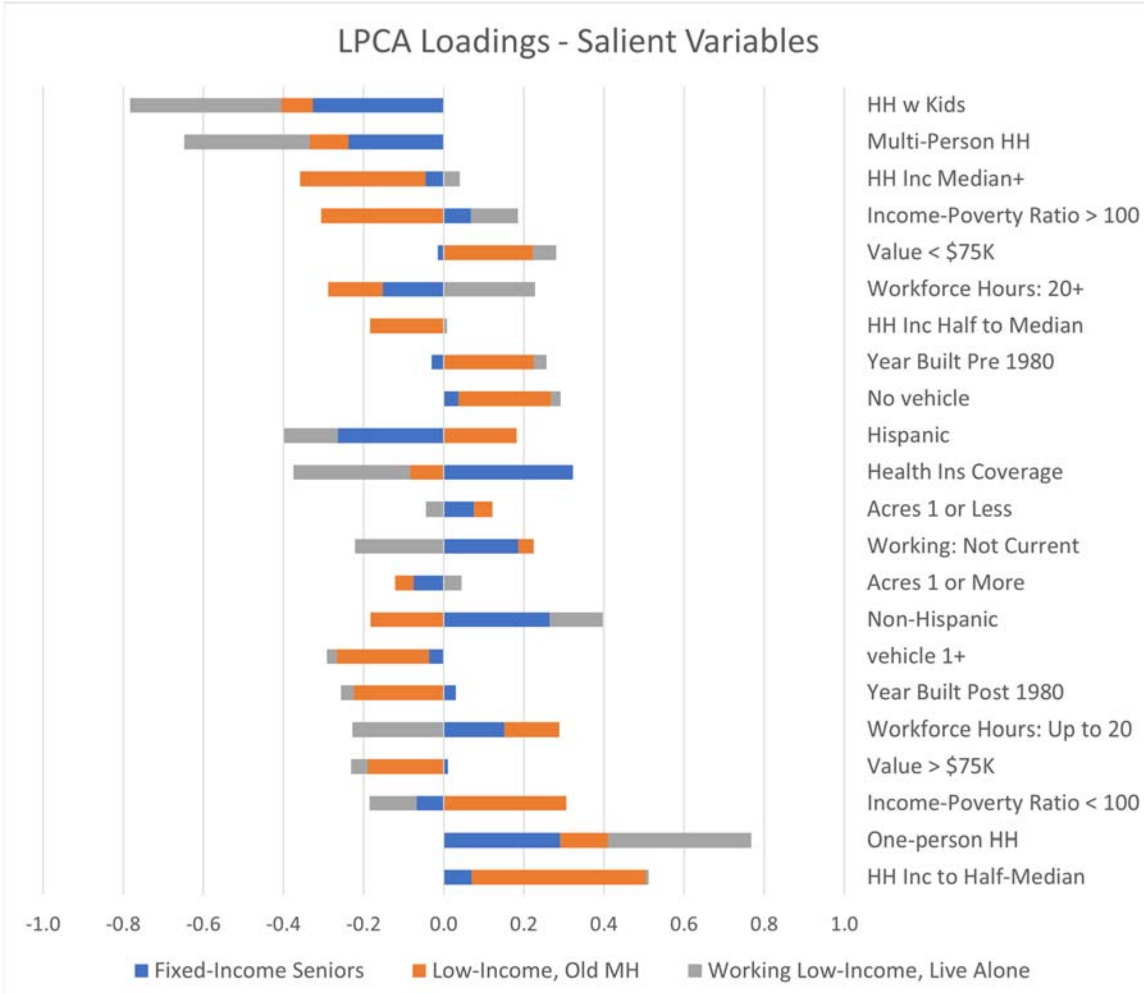


Figure 7. Salient variables. The LPCA results contain a subset of highly relevant variables. Interesting patterns emerge from combining loadings from this subset of variables. For many variables, loadings for all three components (household profiles) have the same sign. This pattern reveals information about the differences among each of the components across the range of salient variables.

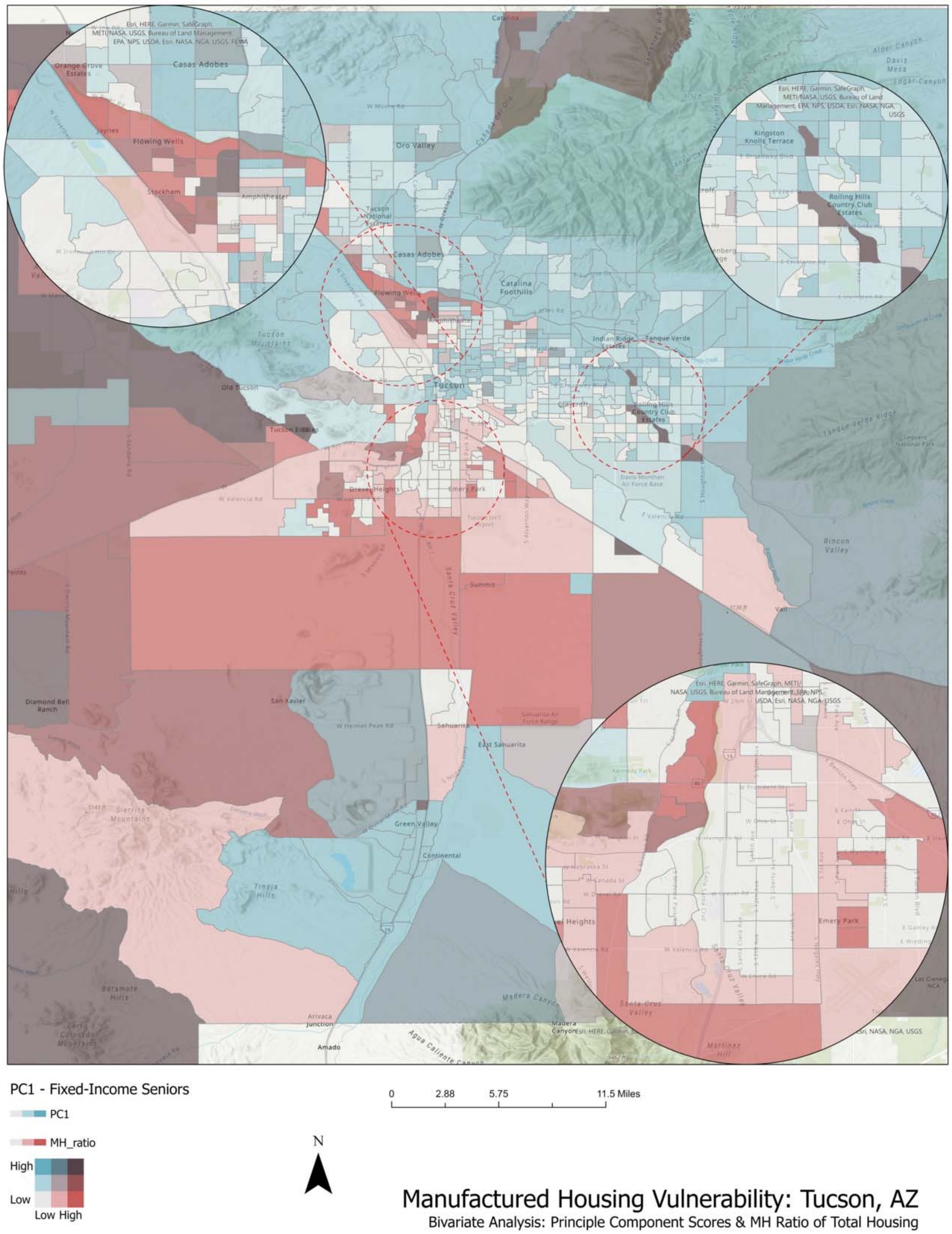


Figure 8. PC 1: Fixed Income Seniors. Map with insets of high-relevance areas in Tucson, AZ.

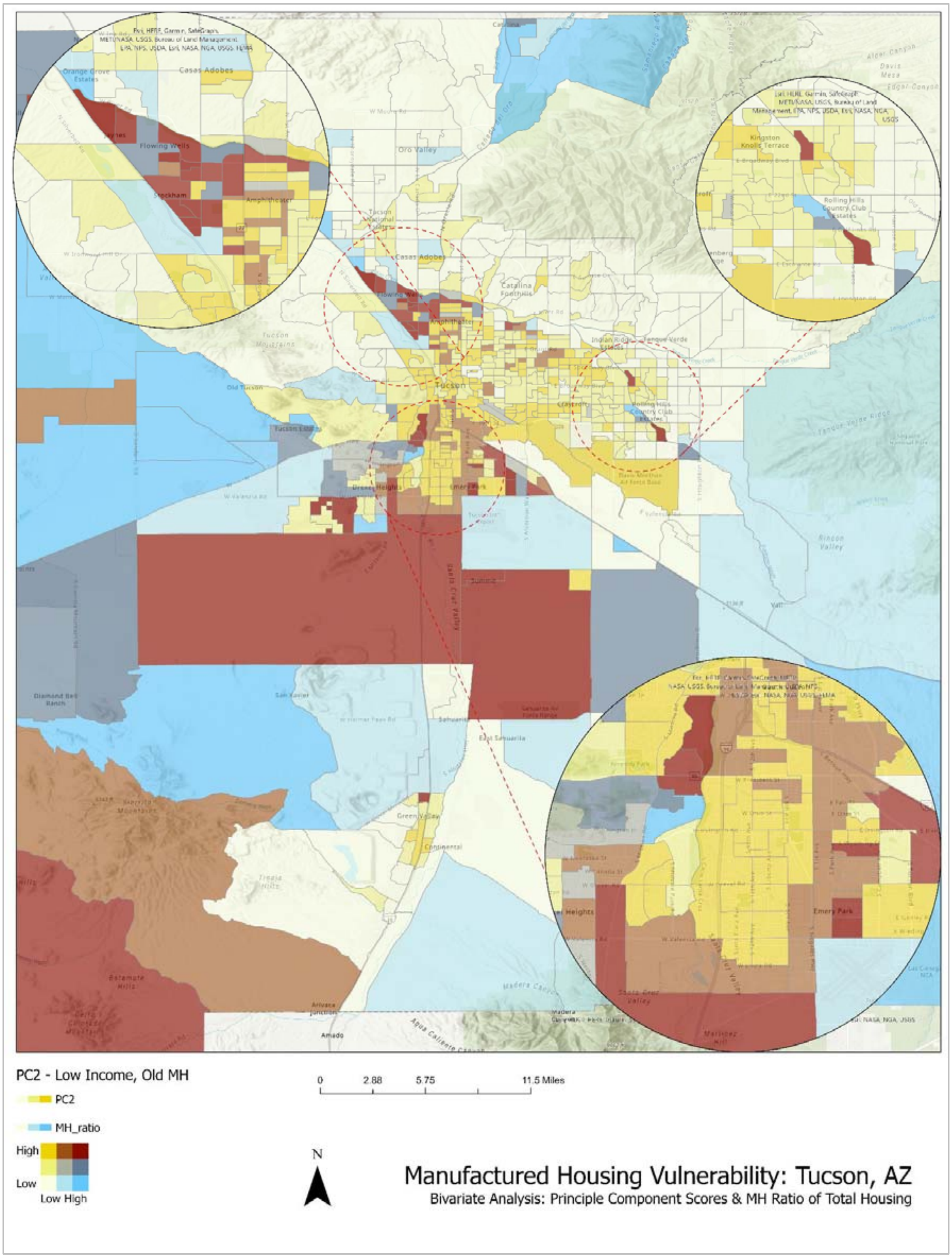


Figure 9. PC2: Low-Income households in older Manufactured Housing. Map with insets of high-relevance areas in Tucson, AZ.

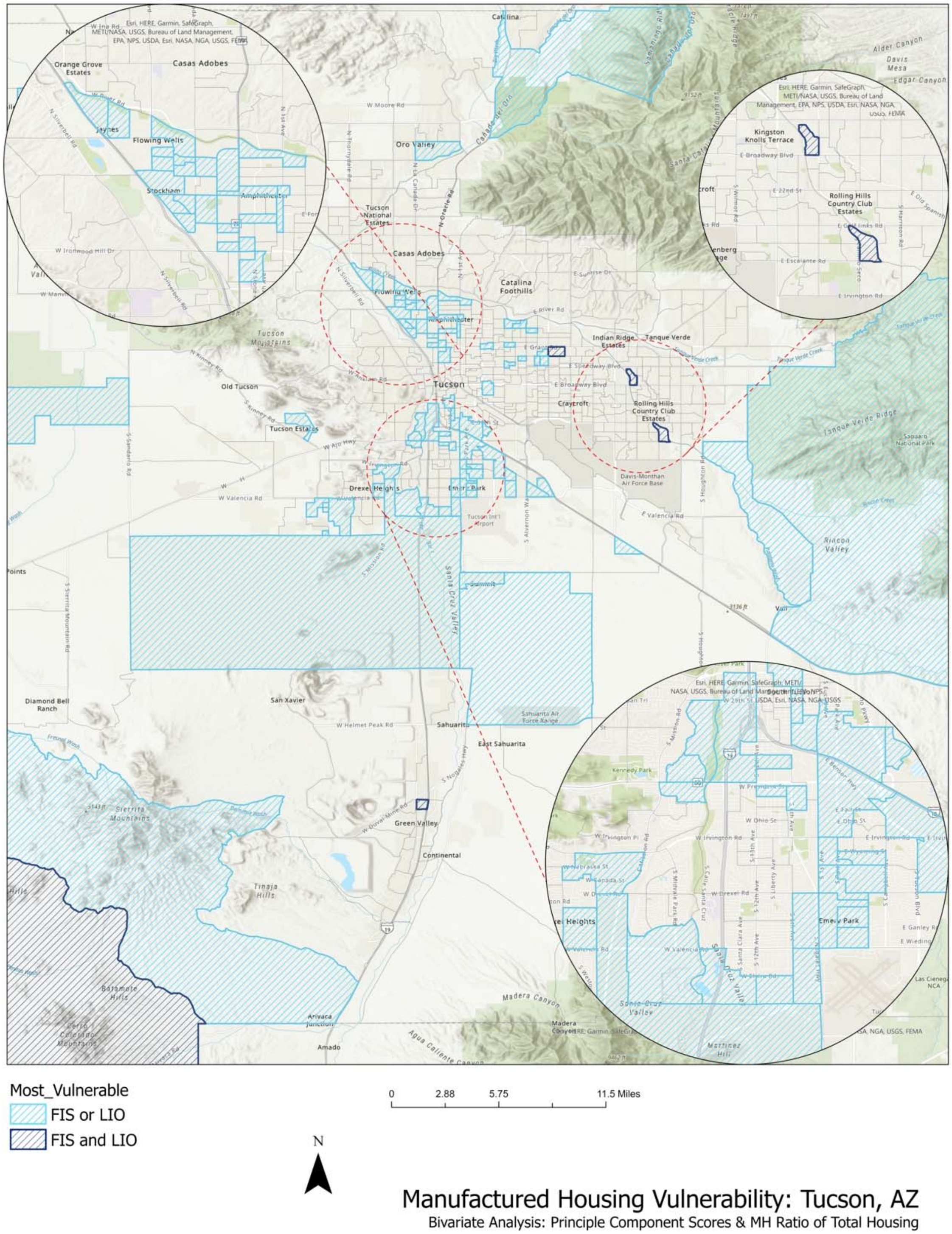


Figure 10. Most Vulnerable CBGs: This figure details the locations where statistically significant bivariate relationships exist between high component scores and MH presence (measured by the MH Ratio) in a CBG. The scale of 0 to 2 comprises the number of components that are statistically significant for each CBG. Therefore, if a CBG has a "most vulnerable" score of 2, the score indicates that 2 components are significant for that CBG. Put in less technical terms, this means that CBGs highlighted in Figure B1 are those where we expect there to be high levels of LIO and FIS MH profiles, and they do not spatially overlap at statistically significant levels.

What These Maps Tell Us About MH Vulnerability

Our map series displays component scores for the two "vulnerable" MH profiles (LIO and FIS) by CBG. High component/profile scores indicate high presence of households with characteristics that align with our different understandings of vulnerability for both FIS and LIO profiles.

The maps highlight the importance of locational context to vulnerability of various kinds. Areas with high MH ratios are mostly isolated in relatively peripheral locations in compact formations, clustering together. A large percentage of Tucson's urbanized area has no presence of MH at all. This isolates MH residents from other profiles, and to some degree reduces their access to regional amenities and needed resources. Recent research about location affordability and transportation costs have suggested that a lower level of accessibility requires more travel time and makes it more costly to shop, go to the doctor, or commute to work (Acevedo-Garcia et al. 2016; Renne et al. 2016).[16] Low accessibility is exacerbated by the poverty of many MH households, as they pay relatively more for transportation as a percent of their income.

As seen in the "most vulnerable" map (Figure *10*) the most common vulnerability designation for CBGs was "1" (meaning that only one component with high scores is significantly related to MH in a CBG). The spatial analysis of high-vulnerability households reveals another important pattern, that of varying degrees of spatial isolation between the different MH vulnerability profiles. The majority of CBGs have only one significant component with high scores, as seen in the map of the "most vulnerable" areas. In other words, most CBGs only have a score of 1 on the "most vulnerable" scale. This suggests that most households from each component profile live in neighborhoods or parks that are largely separate from the other MH profiles. This finding is not an intuitive conclusion that can be drawn from simply observing the maps of each component; rather, it requires isolating those areas with a statistically significant relationship between MH and the component and visualizing them. Many (non-significant) areas in Tucson may not possess a large enough MH population to suggest a special influence stemming from the proximity of each MH profile with another MH profile, or with the general housing stock of Tucson. This analysis helps to identify the locations with the highest prevalence of vulnerable populations.

What the maps tell us about each MH profile is dependent upon the particular vulnerabilities of each profile. For example, seniors are in need of close proximity to health management services and doctor's offices, but likely need less access to job centers relative to other MH occupants. Occupants of old MH need proximity to locations where they can seek refuge from desert heat when their own homes provide insufficient protection.

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[16] See https://www.hudexchange.info/programs/location-affordability-index/. Accessed 7-9-2021.

Conclusions and Next Steps

Mobile and manufactured housing (MH) is arguably Tucson's most important and largest source of unsubsidized affordable housing. However, it is also the nexus of vulnerabilities that can make its residents housing insecure. This white paper aims to help policy makers and housing advocates reconcile with this paradox: to recognize MH's value and importance despite the ways in which it has been marginalized by creating a tool that partials out the MH subpopulations most vulnerable to housing insecurity from the MH population as a whole. Using PCA we were able to identify MH-specific profiles of vulnerability, and then produce mappable indices corresponding to these profiles. This novel approach achieves two broad goals.

First, it avoids reinforcing perceptions of MH as an inherently inferior form of housing, and instead recognizes that MH can be both good and bad housing for highly differentiated populations – like any other housing type. Indeed, Tucson's MH communities contain households that are profiles of both vulnerable and resilient. By recognizing the heterogeneousness of factory-built housing and those who call it home, our approach to indexing vulnerability is a break from how MH has been treated by other social vulnerability indices. Many vulnerability indices use MH as an indicator of vulnerability – suggesting that factory-built housing is a proxy for vulnerability and/or homogeneously correlated with vulnerability. This elision of the complex relationship between MH and vulnerability highlights some of the limitations of broader, more generalized, vulnerability indices.

Second, our approach produces insights that are tailored to specific populations with unique needs. We hope that this will allow local policy makers, service providers and researchers, to better serve and understand the needs of vulnerable groups. Given the non-traditional characteristics of MH and the current lack of a widely accepted evaluation tool for housing insecurity, the ability to zero in on specific populations is particularly valuable.

Limitations and Opportunities

Before considering next steps for this approach to indexing MH vulnerability, it is important to point out some of its limitations. First, population estimates at the CBG level can have large error (Jurjevich and Chun 2021), and despite being more tailored than most indices, ours also misses the considerable heterogeneity that exists at the CBG level. For this reason, it is important to study averages but also individual cases. Some areas that are considered less vulnerable overall may still have specific issues that affect a certain segment of the population in an otherwise resilient area (Murphy and Scott 2014). Moreover, vulnerability within the profiles we have identified is not uniform, and there are subgroups that we know are well represented in MH (those coping with addiction and recovery, those with criminal records, undocumented, etc.) who have fewer housing choices, but are not represented explicitly in our index or profile groups. Our index provides a novel assessment of vulnerability within a particular housing subtype. Finally, it is important to note that available census data do not distinguish between MH registered as real or personal property. Given the aforementioned financial barriers and differential treatment of MH classified as personal property we expect that owners and renters of MH classified as personal property to be more vulnerable on average than owners of MH classified as real property. Thus, while our index provides the depth necessary to assess relative vulnerability among MH residents, it paints an incomplete picture. As a result, our predicted vulnerabilities may understate the vulnerability of certain MH residents whose homes are classified as personal property and underscores the importance of a more complete data collection approach with respect to MH residents. These maps, and arguably all spatial representations of vulnerability indices, should be applied heuristically and not treated as a perfect picture of reality. These limitations speak to the merits of our iterative research design and method. This index has helped us identify gaps (for example, the need to better understand working people living alone in MH), but those gaps remain to be filled in by future research and through the refinement of the index.

The method we developed and applied to Pima County can be similarly applied to other geographies, including Tucson's peer cities. This will allow comparative work on MH. The use of PCA to create indices will allow this comparative research. This research will consider both the extent of MH vulnerability across different geographies, but also how the correlation and characteristics of vulnerability vary from place to place. For example, do profiles resembling LIO and FIS reoccur, or do new profiles emerge?

With composite variables representing MH vulnerability, we are now better positioned to ask questions about how MH vulnerability has changed over time, varies by socioeconomic status and other household characteristics, and to use inferential techniques to better determine its causes and the potential effects of policy interventions (e.g., regression analysis).

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Appendix for “A Profile-Based Approach to Indexing Housing Vulnerability in Tucson: A Case Study of Manufactured Housing”

Appendix A. Descriptive Tables

Table *A1*. Variables Included in Analysis

Original PUMS Variable Name	PUMS Variable Description	Binary Conversions & Thresholds	Used in LPCA
RT	PUMS Record Type (Housing; Group Quarters)	N/A	
SERIALNO	Housing unit/Group Quarters person serial number	N/A	
DIVISION	Division code based on 2010 Census definitions	N/A	
PUMA	Public use microdata area code (PUMA) based on 2010 Census definition (areas with population of 100,000 or more, use with ST for unique code)	N/A	
REGION	Region code based on 2010 Census definitions	N/A	
ST	State Code based on 2010 Census definitions	N/A	
ADJHSG	Adjustment factor for housing dollar amounts (6 implied decimal places)	N/A	
ADJINC	Adjustment factor for income and earnings dollar amounts (6 implied decimal places)	N/A	
WGTP	Housing Unit Weight	N/A	
NP	Number of persons in this household	1-Person (1,0); 2 or more people (1,0)	X
AGEP	Age (Years)	Age 39-64 (1,0); Age >= 65 (1,0)	X
TYPE	Type of unit (Housing unit; Institutional group quarters; Noninstitutional group quarters)	N/A	X

ACR	Lot size (Acres)	1 acre or less (1,0); Greater than 1 acre (1,0)	X
BLD	Units in structure (N/A; Mobile home or trailer; One-family house detached; One-family house attached; Number of Apartments)	Dropped from variables	
ELEFP	Cost of electricity for house during the previous month (USD)	Dropped from variables	
ELEP	Electricity cost (monthly cost, use ADJHSG to adjust ELEP to constant dollars)	The local median cost of electricity or above (1,0)	X
GASFP	Cost of gas for house during the previous month (USD)	Dropped from variables	
GASP	Gas cost (monthly cost, use ADJHSG to adjust GASP to constant dollars)	The median cost of gas or above (1,0)	X
MHP	Mobile home costs (Yearly USD)	Dropped from variables	
RNTP	Monthly rent (use ADJHSG to adjust RNTP to constant dollars)	Dropped from variables	
RWAT	Hot and cold running water (NA; Yes; No; Case is from Puerto Rico and N/A)	Binary; no running water (1,0)	X
TEN	Tenure (N/A; Owned with mortgage or loan (include home equity loans); Owned free and clear; Rented; Occupied without payment of rent)	Renter Occupied (1,0); Owner Occupied (1,0)	X
VACS	Vacancy status (N/A; For rent; Rented, not occupied; For sale only; Sold, not occupied; For seasonal/recreational/occasional use; For migrant workers; Other vacant)	Dropped from variables	
VALP	Property value (NA; $1 to $9999999 (Rounded and top-coded)	At or above $75K (1,0); Below $75K (1,0)	X
VEH	Vehicles (1 ton or less) available (1-6+ vehicles)	No vehicles (1,0); 1 or more vehicles (1,0)	X

WATFP	Cost of water and sewer for home over the last twelve months. (USD)	Dropped from variables	
WATP	Water cost (yearly cost, use ADJHSG to adjust WATP to constant dollars)	Dropped from variables	
YBL	When structure first built (NA; Years 1939-2018)	Structure Built Before 1980 (1,0); Structure Built 1980 or after (1,0)	X
GRPIP	Gross rent as a percentage of household income past 12 months (NA; 1% to 100%; 101% or more)	Dropped from variables	
HHT	Household/family type (N/A (GQ/vacant); Married couple household; Other family household: Male householder, no spouse present; Other family household: Female householder, no spouse present; Nonfamily household: Male householder: Living alone; Nonfamily household: Male householder: Not living alone; Nonfamily household: Female householder: Living alone; Nonfamily household: Female householder: Not living alone)	1-Person HH (1,0); Multi-person HH (1,0);	X
HINCP	Household income (past 12 months, use ADJINC to adjust HINCP to constant dollars)	HH income <= half-median (1,0); HH income half-median to median (1,0); HH income >= area median (1,0)	X
HUPAC	HH presence and age of children (N/A; With children under 6 years only; With children 6 to 17 years only; With children under 6 years and 6 to 17 years; No children)	HH with children (1,0)	X
R65	Presence of persons 65 years and over in household (unweighted) (NA; 0-2+ persons)	Dropped from variables	
SVAL	Specified owner unit (N/A (GQ/ vacant units, except 'for-sale-only' and 'sold, not occupied'/not owned or being bought); A single family home on 10 or more acres or any other type of building, including mobile homes, with no regard to acreage; A single family home on less than 10 acres)	Dropped from variables	
FMHP	Mobile home costs (Yearly USD)	Dropped from variables	
JWMNP	Travel time to work (Minutes)	Dropped from variables	

JWRIP	Vehicle occupancy (NA; 0-10+ person carpool)	Dropped from variables	
JWTR	Means of transportation to work (N/A; Car, truck, or van; Bus or trolley bus; Streetcar or trolley car (carro publico in Puerto Rico); Subway or elevated; Railroad; Ferryboat; Taxicab; Motorcycle; Bicycle; Walked; Worked at home; Other method	Dropped from variables	
MIG	Mobility status (N/A; Yes, same house (non-movers); No, outside US and Puerto Rico; No, different house in US or Puerto Rico)	Migration: Stayers (1,0)	X
SCHL	Educational attainment (NA; No school; Preschool; K-12 Grade levels; 12th grade - no diploma; Regular high school diploma; GED or alternative credential; Some college, but less than 1 year; 1 or more years of college credit, no degree; Associate's degree; Bachelor's degree; Master's degree; Professional degree beyond a bachelor's degree; Doctorate degree)	Ed. Attainment: Higher Ed. (1,0)	X
SEX	Sex (Male, Female)	Dropped from variables	
WKHP	Usual hours worked per week past 12 months (NA; 1-99+ hours)	Weekly Workforce Hours >= 20 (1,0); Weekly Workforce Hours > 20 (1,0)	X
WKL	When last worked (N/A; Within the past 12 months; 1-5 years ago; Over 5 years ago or never worked)	Currently Employed (1,0)	X
HICOV	Health insurance coverage recode (With Health Insurance; Without Health Insurance)	Health Insurance Coverage (1,0)	X
HISP	Recoded detailed Hispanic origin (See US Census for extensive list)	Hispanic (1,0); non-Hispanic (1,0)	X
POVPIP	Income-to-poverty ratio recode (Below 501 Percent; 501+ Percent)	Income-Poverty Ratio < 100 (1,0)	X
RAC1P	Recoded detailed race code (See US Census for extensive list)	White (1,0); Non-White (1,0)	X

This table lists the PUMS variables in their original form, our recoded versions of the variables, and whether they were included in our analysis.

Table *A2*. Descriptive Statistics

Variable Name	Mean	Median	Min.	Max.	Mean	Median	Obs.
Electric cost	119.9	100	4.0	620.0	119.9	100.0	2,122
Gas cost	57.92	40	4.0	400.0	57.92	40.0	2,122
Rent	615.1	550	4.0	2900.0	615.1	550.0	2,122
HH income	42,324	32,600	-6,200	478,400	42,324	32,600	2,122
People in HH	2.046	2.0	0.0	10.0	2.046	2.0	2,122
Acres	1.311	1.0	1.0	3.0	1.311	1.0	2,122
Electric cost flag	2.912	3.0	1.0	3.0	2.912	3.0	2,122
Gas cost flag	3.661	4.0	1.0	4.0	3.661	4.0	2,122
Running water	1.027	1.0	1.0	2.0	1.027	1.0	2,122
Tenure	1.943	2.0	1.0	4.0	1.943	2.0	2,122
Property Value	58,930	40,000	150.0	2,487,000	58,930	40,000	2,122
Number of vehicles	1.597	1.0	0	6.0	1.597	1.0	2,122
Water flag	2.577	3.0	1.0	3.0	2.577	3.0	2,122
Water cost	447.9	360.0	4.0	3800.0	447.9	360.0	2,122
Year built	6.288	6.0	1.0	22.0	6.288	6.0	2,122
HH type	3.257	3.0	1.0	7.0	3.257	3.0	2,122
HH by # kids	3.617	4.0	1.0	4.0	3.617	4.0	2,122
Householder age	60.51	62.0	16	94.0	60.51	62.0	2,122
Commute time	25.82	20.0	1.0	145.0	25.82	20.0	2,122
Commute size	1.168	1.0	1.0	7.0	1.168	1.0	2,122
Commute mode	2.383	1.0	1.0	12.0	2.383	1.0	2,122
Migration	1.23	1.0	1.0	3.0	1.23	1.0	2,122
Educational Attainment	17.14	18.0	1.0	24.0	17.14	18.0	2,122
Sex	1.524	2.0	1.0	2.0	1.524	2.0	2,122
Work hrs. per week	32	36	1.0	99	32	36	2,122
Last time worked	1.928	2.0	1.0	3.0	1.928	2.0	2,122
Health insurance coverage	1.113	1.0	1.0	2.0	1.113	1.0	2,122
Hispanic	1.567	1.0	1.0	24.0	1.567	1.0	2,122
Income-poverty ratio	232.2	203.0	0	501.0	232.2	203.0	2,122
Race	1.786	1.0	1.0	9.0	1.786	1.0	2,122

Appendix B. Confirmatory Analysis

Figure *B1*. K-Means Cluster Analysis: Optimal Clusters

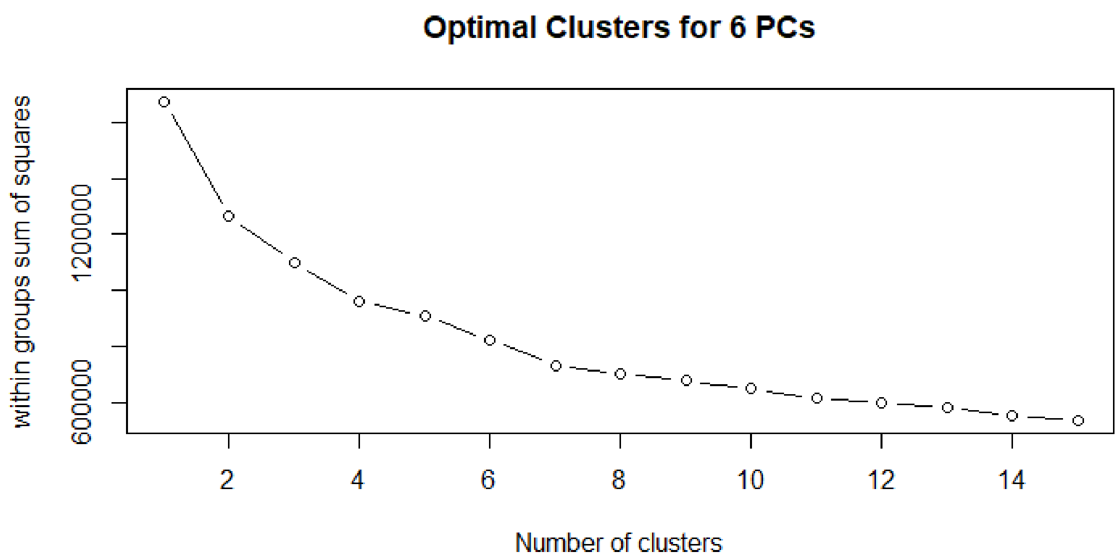
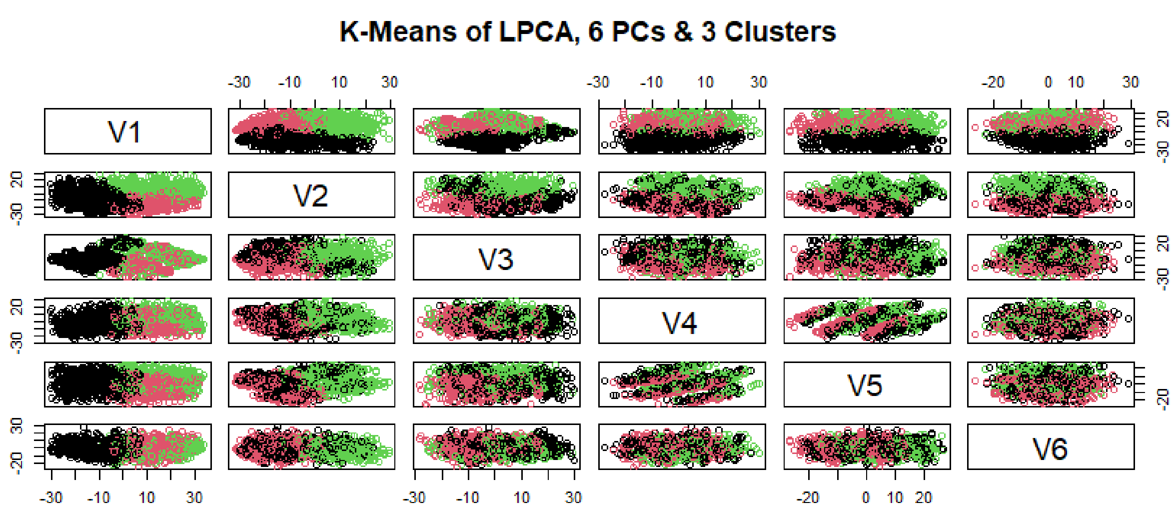
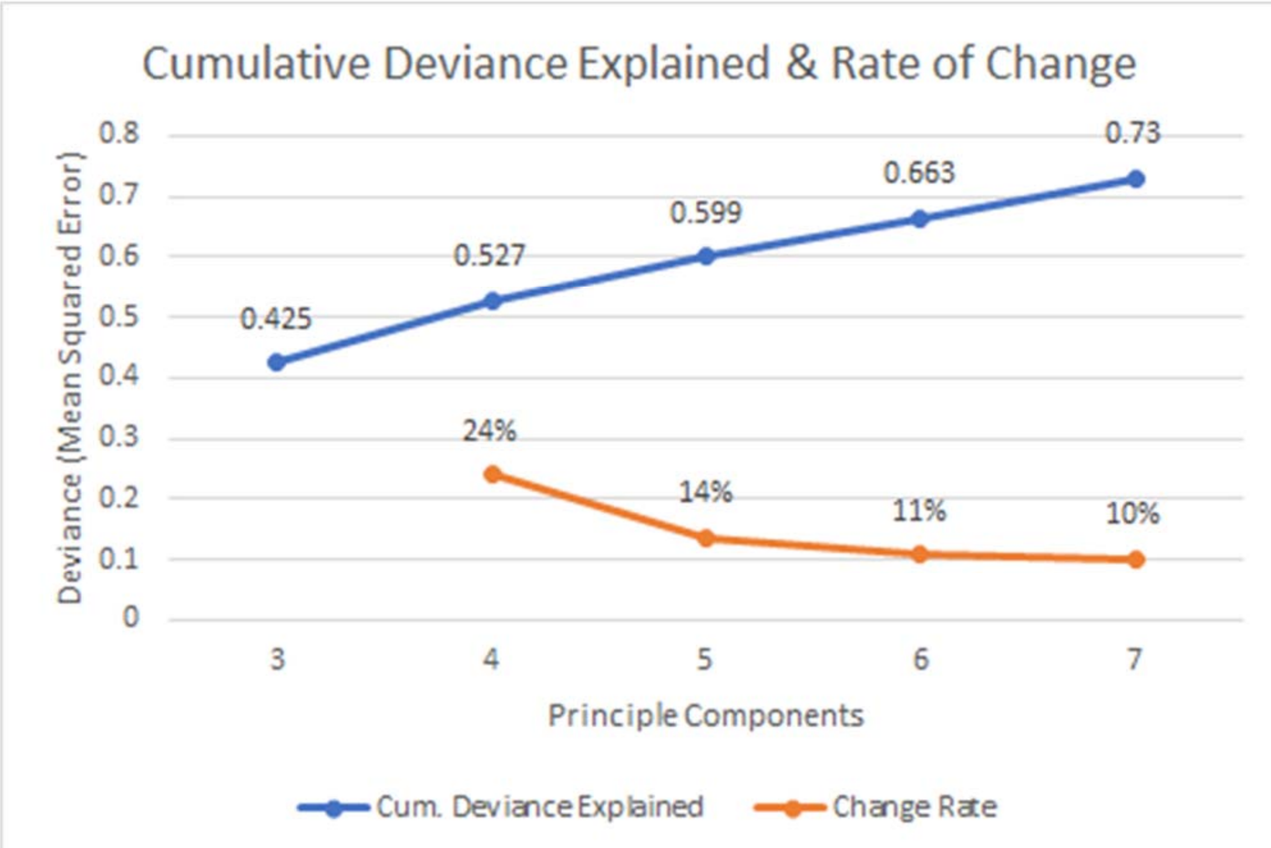


Figure *B2*. K-Means Cluster Analysis: Within-groups Sum of Squares (WSS) Test



WSS test suggests that four clusters is optimal. However, K-means clustering output shows three, not four, PCs with discernible clusters, all within the first three PCs, labeled as V1 through V3. The above plot showed more clearly distinct clustering than the 4-cluster plot. The WSS plot suggests that there is not a large difference in variance between 3 and 4 clusters.

Figure *B3.* Cumulative Deviance Explained



Cumulative Deviance Explained (mean squared error) and the rate of change indicate that 6 components is a suitable choice of components. Research recommends choosing the number of components that capture a sufficiently high amount of total deviance (Landgraf & Lee 2015).