MUCH ADO ABOUT AFFORDABILITY: EXAMINING THE INTERSECTION OF PURCHASE AFFORDABILITY AND NEIGHBORHOOD OPPORTUNITY

A Dissertation

by

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ABSTRACT

Homeownership comprises the largest source of household wealth—and debt—in the U.S. The ability of the vast majority of households to attain homeownership stems primarily from the myriad programs and policies promulgated by the federal government to facilitate purchase affordability—the primary prerogative of federal housing policy. Federally-backed mortgages—FHA-insured, VA-guaranteed, and RHS-guaranteed loans—play a prominent role in achieving such an aim. Federally-backed mortgages significantly ease the affordability of homeownership, particularly for low-income and minority households, by loosening the borrowing constraints—the LTV ratio, DTI ratio, and credit score—required to qualify for a mortgage loan.

Housing planners, policymakers, and practitioners frequently utilize indicators of housing affordability. However, these indicators generally frame affordability as an independent concept, ignoring its indelible relationship with neighborhood opportunity, despite considerable attention devoted by federal housing policy to each topic. The positive correlation between purchase affordability and neighborhood opportunity indicates that federally-backed mortgages, while enhancing affordability, may still largely constrain low-income households to low-opportunity neighborhoods—in essence, sacrificing opportunity for affordability.

In Chapter 6, I develop an improved indicator of purchase affordability, the first of its kind to allow the user both to specify the costs of mortgage financing and differentiate affordability across the four primary types of loans—conventional, FHA-insured, VA-guaranteed, and RHS-guaranteed mortgages. In Chapter 7, I use confirmatory factor analysis to

model the relationship between purchase affordability and neighborhood opportunity and examine the effects of federally-backed mortgages on this relationship. In Chapter 8, I introduce a new framework which maps the disparities in the interaction between purchase affordability and neighborhood opportunity by loan type.

Findings indicate that purchase affordability varies considerably across the income distribution and loan types, broadly indicating that existing indicators of purchase affordability fail to sufficiently encapsulate the issue. Purchase affordability proves more favorable for the lowest-income cohorts in Anderson County; in McLennan County and the Austin-Round Rock MSA, the highest-income cohorts. Furthermore, findings suggest that the interaction between purchase affordability and neighborhood opportunity differs within and across the study sites, with less variability evident in Anderson County and greater variability apparent in the Austin-Round Rock MSA.

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NOMENCLATURE

ACS	American Community Survey
CFPB	Consumer Financial Protection Bureau
DTI	Debt-to-income
FHA	Federal Housing Administration
HMDA	Home Mortgage Disclosure Act
HUD	Department of Housing and Urban Development
LTV	Loan-to-value
REC	Texas Real Estate Research Center
RHS	Rural Housing Service
VA	Department of Veterans Affairs

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER I

INTRODUCTION

Perhaps no topic presently proves more pervasive in housing planning and policy circles than that of housing affordability (Galster & Lee, 2020; Rohe, 2017). The widening economic disparity among households across the United States—exacerbated by the COVID-19 Recession—disparately diminishes the ability of particular households—namely, low-income and minority households—to make timely rental and mortgage payments (Amromin et al., 2020; Fazzari & Needler, 2021; Hardy & Logan, 2020). Although affordability encompasses a vast array of topics, traditionally, purchase affordability—the ability of households to attain homeownership—predominates (Beracha & Johnson, 2012). It lies at the heart of federal housing policy, which subsidizes homeownership to the tune of trillions of dollars per year. Federally-backed mortgages, of which FHA-insured, VA-guaranteed, and RHS-guaranteed mortgages comprise the largest share, constitute one of the primary mechanisms by which the federal government promulgates homeownership (McCarty et al., 2019; Schwartz, 2021). In fact, such mortgages represented over 33% of all home purchase mortgage originations nationwide in 2019 (*HMDA Data Publication*, n.d.).

The rationale for the vast involvement of the federal government in the U.S. mortgage market centers on the perceived benefits of homeownership—largely, its wealth-building potential (Boehm & Schlottmann, 2008; Boehm & Schlottmann, 2004; Rohe et al., 2002). Deeply embedded in the America Dream, homeownership characterizes the single largest expenditure item—and source of wealth—for the vast majority of households across the United States, but particularly low-income and minority households (Grinstein-Weiss et al., 2013; Wainer & Zabel, 2020). The Survey of Consumer Finances reported that, in 2019, home purchase mortgages accounted for 68.8% of family debt. The median value of the primary residence of families measured $225,000, far surpassing the median value of other financial and nonfinancial assets, including bonds, stocks, retirement accounts, and business equity. Meanwhile, the median family net worth of homeowners—$255,000—exceeded that of renters—$6,300—over 40-fold (*Federal Reserve Board - Survey of Consumer Finances (SCF)*, n.d.).

Moreover, homeownership remains the primary mechanism by which low-income and minority households build wealth (Herbert et al., 2013; Herbert & Belsky, 2008; Van Zandt, 2007; Wainer & Zabel, 2020). The Survey of Consumer Finances reported that, in 2019, 37.2%, 53.8%, and 64.6% of families in the less than 20th percentile of income cohort, 20-39.9th percentile of income cohort, and 40-59.9th percentile of income cohort, respectively, owned a primary residence. Meanwhile, the vast majority of minority families owned a primary residence in 2019: 45% of non-Hispanic Black or African American households, 84.5% of Hispanic or Latino households, and 81.1% of all other minorities. These figures exceed the proportion of such households that held traditional financial assets, including bonds, stocks, and retirement accounts (*Federal Reserve Board - Survey of Consumer Finances (SCF)*, n.d.).

However, stark income, racial, and ethnic disparities persist in the wealth-building potential of homeowners (Kuebler & Rugh, 2013). The vast majority of households in the U.S.—in 2020, 86%—rely on mortgage financing to purchase a home (Oppler, 2020). Borrowing constraints—of which the DTI ratio, LTV ratio, and credit score rank as the most prevalent—significantly affect both a household’s access to mortgage financing and the maximum home price affordable to a particular household (Acolin, Bricker, et al., 2016; Linneman & Wachter, 1989). Households of lower income, wealth, and/or credit—especially low-income and minority households—generally face greater difficultly in qualifying for conventional mortgage financing. However, by adjusting (i.e., lowering) the borrowing constraints, federally-backed mortgages enhance purchase affordability, thereby enabling historically underserved households to attain homeownership (Jones, 2018; Perl, 2017; Scally & Lipsetz, 2017; Szymanoski et al., 2012). But such mortgages also lead to significant disparities in the maximum home price affordable to borrowers: the prices of homes purchased with federally-backed mortgages tend to measure below those of homes financed through conventional loans, translating into disparities in homeowners' wealth-building potential. In other words, disparities in the income, wealth, and credit among borrowers of different loan types lead to disparities in the maximum home price for which those borrowers may qualify (Goodman et al., 2018; Malmquist et al., 1997).

Such disparities in the maximum home price affordable to borrowers bears disproportionate effects among the loan types on the borrowers' neighborhood choice (Grinstein-Weiss et al., 2011; Van Zandt & Rohe, 2006). Theory generally posits that the correlation between home prices and neighborhoods translates into a dichotomy between purchase affordability and neighborhood opportunity. The lower the maximum home price affordable to a particular borrower, the fewer the number of neighborhoods affordable to that borrower (Heidelberg & Eckerd, 2011). (The reverse also holds true.) As such, the maximum home price affordable to a particular borrower not only affects his/her neighborhood choice, but it also bears significant implications for the ability of the borrower to access amenities and resources, including jobs, schools, public transportation, etc.—as well as the quality of those amenities and resources. The planning literature broadly denotes the latter as "neighborhood opportunity," and broadly characterizes the opportunity embedded within a particular neighborhood along a gradation, from low- to high-opportunity (Gourevitch, 2018; Knaap, 2017). The correlation between home price and neighborhood opportunity would dictate borrowers with federally-backed mortgages purchase homes in neighborhoods of lower-opportunity than borrowers with conventional mortgages.

Federal housing policy bears a long, well-known, racist history of siting minority homeowners in distressed ("low-opportunity") neighborhoods—primarily through restrictive covenants and redlining (Park & Quercia, 2020; Pearcy, 2020). Although neighborhood opportunity remains a key topic of discussion in the realm of subsidized rental housing—mechanized through residential mobility programs, such as Moving to Opportunity, HOPE VI, stipulations on the siting of such housing via LIHTC's Qualified Census Tracts, etc., surprisingly (and disconcertingly), no such similar discussion has yet emerged in the context of federally-backed mortgages, which far exceed the number of subsidized rental units (Acevedo-Garcia et al., 2016; Ellen et al., 2018; Lens & Reina, 2016). Although we seemingly recognize (and appear to want to reconcile) the deleterious ways in which subsidized rental housing can intentionally sequester minority and low-income households to "low-opportunity" neighborhoods, we continue to frame the racist practices and policies promulgated by the federal government via federally-backed mortgages as a past phenomenon, one which ostensibly ended with the repeal of redlining and ensuing reforms in the wake of the 1968 Fair Housing Act (Dawkins, 2015; Massey, 2015). Failing to frame federally-backed mortgages in the context of neighborhood opportunity presents a myriad of problems—the most significant of which may perhaps prove that we unintentionally persist in perpetuating a legacy perhaps erroneously presumed to be longgone: segregating borrowers with federally-backed mortgages to low-opportunity neighborhoods.

This dissertation seeks to bridge the current gap in the literature between purchase affordability and neighborhood opportunity, particularly in the context of federally-backed mortgages. Following an overview of FHA-insured, VA-guaranteed, and RHS-guaranteed mortgages—including the characteristics of borrowers and loans—I delve into an intensive literature review on purchase affordability and neighborhood opportunity, particularly, the primary methods to measure each: indicators of purchase affordability and opportunity mapping. The conclusions of the literature review guide the development of a new, comprehensive framework which integrates purchase affordability and neighborhood opportunity.

Firstly, I empirically derive a new method to measure purchase affordability, the Losey Indicator of Purchase Affordability. Using data from the American Community Survey, it computes the percentage of homes either over- or under-supplied within a particular income cohort. It uses the terms and costs of mortgage financing as well as the additional costs of homeownership to estimate the maximum home price affordable to a particular income cohort. Preliminary results suggest that this indicator improves on existing indicators, which largely estimate purchase affordability using a more limited set of parameters. Moreover, this indicator is the first of its kind to estimate purchase affordability separately for conventional and federally-backed mortgages, including FHA-insured, VA-guaranteed, and RHS-guaranteed loans.

Secondly, using confirmatory factor analysis, I treat purchase affordability and neighborhood opportunity as latent constructs and explore the relationship between each latent construct and the observed variables which encapsulate it. The model indicates that purchase affordability and neighborhood opportunity do not always bear a positive association, but rather that the direction of the relationship depends on the particular geography of interest. The two appear moderately correlated with each other in all three study sites.

Lastly, using the Losey Indicator of Purchase Affordability and the seven HUD Opportunity Indexes, I empirically derive the Affordability-Opportunity Index, which measures the disparity in the interaction between purchase affordability and neighborhood opportunity within a particular Census tract and its average value for a broader region. The Index forms the basis for the Affordability-Opportunity Mapping Tool, which depicts the interaction between purchase affordability and neighborhood opportunity at the Census tract level using a publicly-available, interactive mapping platform. Users can compare the interaction between purchase affordability and neighborhood opportunity by loan type, which allows users to estimate the effects of changes to mortgage terms on the interaction.

Contribution to Policy

Facilitating housing affordability and neighborhood opportunity concurrently comprises a key objective of planners, policymakers, and practitioners, a result of 1) the perceived benefits of homeownership on households and neighborhoods and 2) the perceived benefits of high-opportunity neighborhoods on inhabitants (Boehm & Schlottmann, 2008; Chetty et al., 2014; Galster, 2017; Herbert et al., 2013). However, the inherent dichotomy between the two particularly complicates such an objective. To meet the dual (and often mutually opposing) objective of facilitating both housing affordability and neighborhood opportunity, planners, policymakers, and practitioners need a framework which measures both simultaneously (Finio et al., 2020; Heidelberg & Eckerd, 2011).

Planners, policymakers, and practitioners frequently rely on quantitative data analysis, such as indexes, maps, and other indicators, to measure the presence and magnitude of perceived problems, inform planning and policy decisions, direct federal, state, or local housing assistance (or procure funding), and compare problems across geographies or over time (Dokko, 2018; Finio et al., 2020; Knaap et al., 2014; Mast, 2015). For instance, the HUD standard—which stipulates that housing is unaffordable for households that spend more than 30% of income on housing costs—serves as the federal standard for housing assistance (Stone, 2006). Meanwhile, recent federal mandates require localities and municipalities to use opportunity maps to measure neighborhood opportunity (Gourevitch, 2018). Such analyses prove a prominent feature of planning reports, which generally guide short- and/or long-term planning decisions. The prevalence of purchase affordability and neighborhood opportunity as planning and policy concerns dictates that the usage of these methods will likely increase over the near-term (Hendey & Cohen, 2017; Silverman et al., 2017).

The two new methods proposed in this research—the Losey Indicator of Purchase Affordability and the Affordability-Opportunity Mapping Tool—present several policy implications. The Losey Indicator of Purchase Affordability denotes the first measure of purchase affordability that allows users to estimate the effects of changes to mortgage financing terms—the mortgage interest rate, loan term, LTV ratio, and DTI ratio, the costs of mortgage financing—for conventional mortgages, private mortgage insurance; for FHA-insured mortgages, annual and upfront mortgage insurance premiums; and for VA-guaranteed and RHS-guaranteed mortgages, the funding fee, and the additional costs of homeownership—property taxes and insurance—on purchase affordability. It also ostensibly serves as the first indicator to differentiate purchase affordability across the loan types. Moreover, the indicator allows housing planners, policymakers, and practitioners to define income cohorts of interest to them, compute the indicator, and readily identify cohorts which face an undersupply of housing. This could inform decisions related to directing housing assistance, targeting programs and initiatives, etc. The indicator computes affordability separately for conventional, FHA-insured, VA-guaranteed, and RHS-guaranteed mortgages, which permits users to elucidate the magnitude of potential disparities in affordability across loan types, as well as the implications on the borrowers who seek such mortgages.

Federal housing policy largely predicates the promulgation of purchase affordability (via the federally-backed mortgages) on the notion that 1) renters who attain homeownership move into higher-opportunity neighborhoods and 2) homeownership correlates positively with neighborhood opportunity. In other words, such policy is founded on the premise that homeowners make better neighbors and build better neighborhoods (Herbert et al., 2013; Rohe et al., 2002; Wainer & Zabel, 2020). The Mapping Tool provides the first quantitative measure of the interaction between purchase affordability and neighborhood opportunity, potentially allowing planners, policymakers, and practitioners to assess the normative standards on which homeownership is founded.

The Mapping Tool allows users to identify differences among the loan types in the interaction between purchase affordability and neighborhood opportunity and to elucidate these differences across the income distribution or specific income cohorts. Moreover, as the

Affordability-Opportunity Index embedded in the mapping tool partially acts as a function of the Losey Indicator of Purchase Affordability, planners, policymakers, and practitioners can use the mapping tool to anticipate how changes in purchase affordability across the loan types will affect the interaction between purchase affordability and neighborhood opportunity. In other words, users can assess whether, for example, increasing purchase affordability within a particular Census tract would enable households to gain access to higher-opportunity neighborhoods.

Contribution to Theory

Within housing and community development circles, considerable contention continues to enshroud the intersection of housing affordability and neighborhood opportunity (Bourassa & Haurin, 2017; Galster, 2017b). The nature of the relationship between the two topics—i.e., inverse—indicates that planners, policymakers, and practitioners generally face a significant tradeoff in decisions on household mobility, the siting of housing, and the distribution of resources. Historically, tension arose among scholars and activists over the perceived merits of encouraging relocation to higher-opportunity neighborhoods vs. investing in the lower-opportunity neighborhoods home to those residents (Galster, 2017a; Owens, 2017). The normative standards imposed by the federal government over the past near-century on the neighborhoods inhabited by recipients of subsidized rental housing typically favored relocation; however, recent policy actions at the federal level, including Obama's Promise and Choice Neighborhoods, perhaps portend the reversal of such a trend (Goetz, 2015; Smith, 2011). Indeed, this enduring debate sparked a long litany of literature which documents the effects of neighborhoods on recipients of subsidized rental housing, especially participants of housing mobility programs (Davidson, 2009; Turner, 2017).

However, at present, such a debate fails to permeate federal policy on homeownership. The historical racist practice of redlining notwithstanding, the federal government continues to maintain its decades-long sole focus on purchase affordability, seemingly unattuned to the undeniable intersection between homeownership and neighborhood opportunity (Heidelberg & Eckerd, 2011; McCarty et al., 2019). As the primary promulgator of opportunities for homeownership—via federally-backed mortgages—the federal government plays a significant role in determining the neighborhoods in which recipients of such mortgages can purchase homes (Bhutta, 2012). Adjusting the borrowing constraints—i.e., increasing or decreasing purchase affordability—can lead to considerable changes in the maximum home price affordable to a particular household, which bear significant implications for the neighborhoods affordable to borrowers (Acolin, Bricker, et al., 2016; Duca & Rosenthal, 1994; Zorn, 1989, 1993). The literature review for this dissertation consists of two chapters: 1) an overview of federally-backed mortgages, with particular attention paid to FHA-insured, VA-guaranteed, and RHS-guaranteed mortgages and 2) an overview of housing affordability and neighborhood opportunity, focused on indicators of owner-occupied housing affordability (i.e., methods by which to operationalize affordability) and opportunity mapping.

Chapter Structure

Chapter 2 provides an overview of federally-backed mortgages, while Chapter 3 reviews the literature on the two key topics interwoven throughout this research: housing affordability—

with particular attention paid to indicators of owner-occupied housing affordability—and neighborhood opportunity—with a specific focus on the practice of opportunity mapping. Chapter 4 describes the methodology used to develop an improved indicator of purchase affordability, model the relationship between purchase affordability and neighborhood opportunity, and build a new mapping tool which depicts the interaction between purchase affordability and neighborhood opportunity. Chapter 5 presents the preliminary data analysis; Chapters 6-8 present the research findings for each of the three research questions, and Chapter 9 discusses the conclusions and policy implications.

Chapter 2 provides an overview of the three most prevalent federally-backed mortgages: FHA-insured, VA-guaranteed, and RHS-guaranteed mortgages. It reviews the history and purpose of each type of mortgage, any eligibility requirements, and the characteristics of borrowers and loans, including the credit score and DTI and LTV ratios. It also describes the neighborhood characteristics considered in the mortgage loan origination process.

Chapter 3 reviews the literature on housing affordability and neighborhood opportunity. With respect to the former, the chapter presents definitions and indicators of housing affordability; specifically, owner-occupied housing affordability. It discusses the conceptual and methodological limitations presently facing housing affordability; with respect to the latter, criticism focuses on the four most ubiquitous indicators of owner-occupied housing affordability: the HUD Measure, Median Multiple, Housing Affordability Index, and Housing Opportunity Index. This chapter also poses suggestions for an improved indicator of owner-occupied housing affordability.

With respect to neighborhood opportunity, Chapter 3 devotes particular attention to the methodology behind opportunity indexes and opportunity mapping and the limitations embedded in those methods. It frames this discussion in the context of the recent push by the federal government to encourage localities and municipalities to Affirmatively Further Fair Housing (AFFH) (Silverman et al., 2017). The focus of federal policy on neighborhood opportunity over the past decade-plus, coupled with its long-enduring objective to facilitate purchase affordability, dictates a critical review of the methods by which planners, policymakers, and practitioners operationalize such topics.

Chapter 4 describes the methodology used in this research. In addition to the cross-sectional research design used in this dissertation, this chapter discusses the process of data cleaning, transforming and recoding the variables, and study limitations. Chapter 5 provides a descriptive analysis, via descriptive statistics and maps, of the characteristics of borrowers, loans, and neighborhoods by loan type. This analysis undergirds the findings.

Chapter 6 introduces an improved indicator of purchase affordability—the Losey Indicator of Purchase Affordability. This indicator reflects the most important characteristics of mortgage financing—the LTV and DTI ratios, interest rate, loan term, and loan fees, such as upfront and annual fees. It also incorporates the additional costs of homeownership, such as property taxes and insurance. This chapter computes the results of the indicator for conventional, FHA-insured, VA-guaranteed, and RHS-guaranteed mortgages within the three study sites. Findings indicate that the indicator performs better than the Median Multiple, one of the most popular indicators of purchase affordability.

Chapter 7 uses structure equation modeling—specifically, confirmatory factor analysis—to examine the relationship between purchase affordability and neighborhood opportunity. This model identifies the particular variables which affect the relationship, as well as the direction of that effect and its magnitude. Findings indicate that, among the three study sites, on average, property value and the borrower's income denote the two most significant components of purchase affordability.

Chapter 8 presents a new method—presumably, the first of its kind—to model the interaction between purchase affordability and neighborhood opportunity simultaneously: the Affordability-Opportunity Mapping Tool. Chapter 9 discusses the conclusions and policy implications of this research, as well as recommendations for future research.

CHAPTER II

OVERVIEW OF FEDERALLY-BACKED MORTGAGES

Homeownership is virtually synonymous with mortgage financing (Acolin, Bricker, et al., 2016; Green & Wachter, 2005; Linneman & Wachter, 1989). The vast majority of households in the United States rely on mortgage financing to attain homeownership—in 2020, 86% of homebuyers used a mortgage loan to purchase a home (Oppler, 2020). Mortgage loans broadly fall into two categories: conventional or federally-backed mortgages (Baeck & DeVaney, 2003). Generally, federally-backed mortgages—of which Federal Housing Administration (FHA), Department of Veterans Affairs (VA), and Rural Housing Service (RHS) loans comprise the overwhelming majority—serve borrowers who lack sufficient income, wealth, or credit to qualify for conventional mortgage financing (Gabriel & Rosenthal, 1991; LaCour-Little, 2007; McCarty et al., 2019). While conventional loans remain the primary source of mortgage financing, federally-backed mortgages extend mortgage credit to populations underserved by conventional mortgages, including low-income, minority, and first-time homebuyers (Acolin, Bricker, et al., 2016; Baeck & DeVaney, 2003; Malmquist et al., 1997).

Conceived in the midst of the Great Depression, federally-backed mortgages played a crucial role in the transition from a nation of primarily renters to one of mostly homeowners (Green & Wachter, 2005). During the administration of President Franklin D. Roosevelt, the massive restructuring of the mortgage financing system—principally, the creation of the secondary mortgage market—bore first the FHA-insured mortgage in 1934, followed in the late 1930s by the precursor to the modern-day RHS-guaranteed mortgage, and finally, toward the end of World War II, the VA-guaranteed mortgage (Carliner, 1998; Fishback et al., 2001; Hirsch, 2000; Scally & Lipsetz, 2017). These mortgages assisted in reducing the financial barriers to homeownership and allowed a greater proportion of Americans to access mortgage financing, bolstering the homeownership rate from 44% in 1940 to 69% in 2004 (Acolin, Goodman, et al., 2016).

This section will provide a brief overview of federally-backed mortgages; specifically, 1) the rationale of the federal government for the overhaul of the existing mortgage financing system and the creation of the secondary mortgage market, 2) the overarching purpose of federally-backed mortgages, and 3) the ways in which these mortgages enhance the affordability of homeownership. While this dissertation will only briefly review the series of events which contributed to the creation of federally-backed mortgages, several scholars previously published detailed accounts (Hirsch, 2000; Rose, 2011; Rose & Snowden, 2013; Snowden, 2010; Van Order & Yezer, 2014). Although necessarily short and by no means comprehensive, such an overview situates readers within the broader framework of purchase affordability—i.e., the role of the federal government in leveraging mortgage financing to enhance the affordability of homeownership. This section will then delve into the particulars of the three most ubiquitous federally-backed mortgages, including eligibility requirements and the characteristics of borrowers and loans. This section will conclude with an overview of the characteristics of neighborhoods considered in the origination process of the federally-backed mortgages.

History

The first federally-backed mortgage (the FHA-insured mortgage) was borne amidst the greatest economic downturn in the history of the U.S.—the Great Depression (although, as of this writing, the COVID-19 Recession certainly threatens to usurp its title) (Spatt, 2020; Van

Order & Yezer, 2014). The Great Depression signaled an unprecedented period of economic decline in the United States, which spelled disaster to a variety of industries and entities, but proved particularly deleterious for the nation's housing market. Significant disruptions to the labor market, including a precipitous spike in the unemployment rate, left a large portion of existing homeowners unable to make timely mortgage payments (Rose, 2011; Wheelock, 2008b).

Until the 1930s, mortgage financing was largely inaccessible to the average American. Mortgage loans were primarily originated by local banks, such as savings and loans and credit unions, which did not boast sufficient underlying assets as to assume large levels of risk. To mitigate borrower risk, banks required large downpayments (40 to 50 percent of home value) and balloon payments at the end of the loan term, which generally lasted two- to five-years. Most households, lacking sufficient capital reserves (i.e., wealth) for such a large downpayment, were precluded from accessing mortgage credit (Getter, 2021; Rose & Snowden, 2013; Schwartz, 2021). (Homeowners unable to finance the balloon payment in full at the end of the original loan term would generally refinance the remaining lump sum, thereby extending the term of the loan.) This system favored wealthier households (i.e., those who could afford the large downpayment and demonstrated to lenders an ability to repay the mortgage) (White, 2014). Indeed, prior to the Great Depression, the United States was largely a nation of renters, who represented three-fifths of all households (Wright, 2005).

However, the Great Depression beckoned a period of significant disruption to the nation's housing market: at the beginning of 1934, delinquencies amounted to nearly half of all urban residential mortgages, while the foreclosure rate for such mortgages increased nearly ten percentage points from 1926 (3.6%) to 1933 (13.3%) (Wheelock, 2008b, 2008a). The stock market crash in 1929 and the ensuing banking crisis left lenders unable or unwilling to refinance borrower's balloon payments, instead calling them due upon the end of the loan term (Brocker & Hanes, 2013). This caused massive borrower default (and home foreclosure): staggering levels of unemployment left millions of Americans in dire financial straits. A crumbling economy contributed to declining property values, prompting properties to spiral into negative equity and owners to respond via mortgage default. This process culminated in a ruinous heap: banks, facing a tremendous share of mortgages for which the value of the loan exceeded the collateral (value of the home), simply could not finance new home mortgages (Snowden, 2010; Wright, 2005).

The crisis swirling in the housing market prompted the creation of several programs and policies, initially promulgated by the administration of President Franklin D. Roosevelt, which paved the way for present-day mortgage financing (Getter, 2021; Wheelock, 2008b). These reforms instituted a system of greater liquidity and stability in which the federal government assumes a significant portion of the risk borne by borrowers of federally-backed mortgages, thereby incentivizing private lenders to originate such mortgages (Carrozzo, 2008). In response to the substantial offloading of risk, private lenders demonstrate greater willingness to originate mortgages to "riskier" borrowers—i.e., borrowers of lower wealth, income, and credit. Such a phenomenon increases the accessibility of mortgage financing to households otherwise unable to qualify for conventional mortgages (Fishback et al., 2001; Schwartz, 2021).

The pieces of legislation which initiated the three most prominent federally-backed mortgages include the following:

1) The Federal Housing Act of 1934, which created the FHA-insured mortgage (Gotham, 2000).

2) The Bankhead-Jones Farm Tenant Act of 1937, which provided initial authorization to the U.S. Department of Agriculture (USDA) to provide low-interest, long-term mortgage loans to farmers (Maddox, 1937; Scally & Lipsetz, 2017).

3) The G.I. Bill (also known as the Servicemen's Readjustment Act of 1944) initiated the VA-guaranteed mortgage—"a less expensive alternative to a cash bonus for veterans returning from World War II that would still provide benefits to veterans" (McCarty et al., 2019, p. 24).

Types of Mortgages

The federal government "backs"—i.e., originates, insures, or guarantees—a vast array of home purchase mortgages through three agencies: the FHA, VA, and the USDA, which oversees the RHS. Three of these mortgages—FHA-insured, VA-guaranteed, and RHS-guaranteed loans—presently (and, in the instance of FHA-insured and VA-guaranteed mortgages, historically) prove the most prevalent of the many varieties of federally-backed mortgages (Bhutta et al., 2017b; Foote, 2010a; Getter, 2021). Other types of federally-backed mortgages include the Native American Direct Loan and Section 502 Direct Loans, which currently comprise a relatively small portion of all home purchase mortgage originations. For example, in 2017, the RHS originated approximately 7,000 Section 502 Direct Loans, compared to an estimated 134,000 Section 502 Guaranteed Loans (McCarty et al., 2019). Over the last several decades, the federal government has shifted from direct lending (i.e., originating mortgages) to insuring or guaranteeing loans, symptomatic of its increasing reliance on the private market (Jaffee, 2011). Such a phenomenon dictates heightened attention to FHA-insured, VA-guaranteed, and RHS-guaranteed mortgages. Table 2.1 depicts the prevalence of federally-backed mortgages in the United States from 2005 to 2017.

Table 2.1 The Number of Mortgage Originations by Loan Type (in Thousands)

	FHA-Insured	VA-Guaranteed	USDA Section 502 Guaranteed
2005	323	119	31
2006	295	123	30
2007	317	118	34
2008	845	142	61
2009	1,088	181	133
2010	944	193	133
2011	760	187	130
2012	738	202	145
2013	665	241	163
2014	601	272	136
2015	811	322	134
2016	891	353	117
2017	851	380	134

Source: (McCarty et al., 2019)

Despite slight nuance between insured and guaranteed mortgages, the more notable distinction lies between direct and insured or guaranteed mortgages. In the instance of direct loans, the corresponding entity within the federal government (i.e., the VA or the RHS) acts as the originator of the loan (Delgadillo et al., 2011; Perl, 2017; Scally & Lipsetz, 2017). In other words, direct loans do not involve actors in the private market. Direct loans pose significant risk to the federal government; should the borrower default on his/her loan, the federal government assumes the entire remaining balance of the loan (i.e., the residual mortgage debt). Moreover, borrowers of direct loans may pose more risk to the lender (i.e., the federal government), as the borrowers may bear a greater probability of mortgage default due to lower levels of income, wealth, and credit (Jaffee, 2011; Jones et al., 2017).

With respect to insured versus guaranteed mortgages, in either case, the federal government absorbs a portion of the borrower risk that would otherwise be assumed by the lender. The FHA mortgage insurance program plays a significant role in encouraging private lenders to originate loans to borrowers typically considered uncreditworthy by the private market, namely because of lower wealth, income, or credit. The FHA insurance program insures 100% of the loan—should the borrower default, the federal government will repay the remaining loan balance (Caplin et al., 2015). In other words, in the event the borrower does not repay the loan balance, the FHA reimburses the lender for the unpaid portion of the loan (Jones, 2018; Szymanoski et al., 2012; Van Order & Yezer, 2014). Meanwhile, the VA loan guaranty only reimburses lenders for a portion of the remaining loan balance—generally 25%, but the portion varies by loan amount. The minimum guaranty is $36,000; however, the guaranty, regardless of the portion of the loan amount, cannot surpass the county loan limit (*VA Home Loan Limits | Veterans Affairs*, n.d.) Due to the differential in the proportion of the loss absorbed by the federal government, VA-guaranteed mortgages pose more risk to lenders than FHA-insured mortgages. Unlike FHA-insured mortgages, the lender must assume the loss on the property which exceeds the VA guaranty (Foote, 2010b; Perl, 2017).

Borrowing Constraints

Facilitating the affordability of homeownership undergirds federally-backed mortgages (Baeck & DeVaney, 2003; Foote, 2010b, 2010a; Jones, 2018; Scally & Lipsetz, 2017; Van Order

& Yezer, 2014). Despite the differences in the characteristics of the borrowers, loans, and/or properties eligible for and served by each type of federally-backed mortgage, overarchingly, each seeks to extend mortgage financing to households traditionally unable to qualify for conventional mortgage financing—specifically, low-income, minority, and/or first-time homebuyers (McCarty et al., 2019). As previously mentioned, the overwhelming majority of American households use mortgage financing to purchase a home (Oppler, 2020). Therefore, as attaining homeownership generally necessarily entails ensuring access to mortgage financing, affordability becomes a function of mortgage financing—specifically, the terms dictated by private mortgage lenders. In other words, facilitating affordability is inherently linked to ensuring the access of households to mortgage financing (Duca & Rosenthal, 1994; Linneman & Wachter, 1989).

Federally-backed mortgages enhance purchase affordability by lowering the barriers faced by households in qualifying for a mortgage loan. Lenders consider a myriad of factors in the origination decision (i.e., the decision whether to accept or deny the loan), including the applicant’s employment history, credit history, cash reserves, and other forms of household debt. However, the applicant’s income, wealth, and credit comprise the three primary factors, or borrowing constraints, weighed by lenders (Acolin, Bricker, et al., 2016; Gabriel & Rosenthal, 1991; Linneman & Wachter, 1989). Mortgage lenders evaluate applicant’s income, wealth, and credit through the debt-to-income (DTI) ratio, loan-to-value (LTV) ratio, and credit score, respectively. In the eyes of the lender, higher DTI and LTV ratios and lower credit scores increase the risk posed by the applicant; however, such risk is mitigated through federally-backed mortgages, which, depending on the type of mortgage, insure or guarantee a portion of the loan (Kim et al., 2018; Quercia et al., 2012).

FHA-Insured Mortgages

Since its inception, the FHA has played a particularly prominent role in increasing access to homeownership. In fact, for nearly one century (since 1934), the FHA has served as the single largest insurer of home purchase mortgages in the United States (Jones et al., 2017; Szymanoski et al., 2012). In 2017, FHA-insured mortgages represented 20% of all home purchase mortgages, with over 850,000 originations that year alone (McCarty et al., 2019). The FHA originated 817,847 forward purchase mortgages in FY 2020 and currently maintains a portfolio of over 8 million single-family mortgages. Presently, the FHA namely serves first-time, low- and moderate-income, and minority homebuyers (*Annual Report to Congress on the Financial Status of the MMI Fund | HUD.Gov / U.S. Department of Housing and Urban Development (HUD)*, n.d.)

FHA-insured mortgages dictate both an up-front mortgage insurance premium (1.75% of the base loan amount) and annual mortgage insurance premium. The latter depends on the base loan amount, LTV ratio, and loan term—presently, the annual mortgage insurance premium ranges from 0.45% to 1.05% of the base loan amount. For example, for a borrower with a base loan amount which does not exceed $625,000, an LTV ratio which does not exceed 90%, and a loan term which does not exceed 15 years, the annual mortgage insurance premium equals 0.45% of the base loan amount and must be paid annually for eleven years. Meanwhile, a borrower with a base loan amount which exceeds $625,000, an LTV ratio which does not exceed 90%, and a loan term of over 15 years can expect to pay an annual mortgage insurance premium equal to

1.05% (*Single Family Upfront Premium/Late/Interest | HUD.Gov / U.S. Department of Housing and Urban Development (HUD)*, n.d.).

Eligibility Requirements

With respect to FHA-insured, VA-guaranteed, and RHS-guaranteed mortgages, FHA-mortgages impose the fewest eligibility requirements on borrowers. As such, borrowers who qualify for VA-guaranteed or RHS-guaranteed mortgages may also be eligible for FHA mortgage financing; however, the reverse may not hold true (Baeck & DeVaney, 2003; Goodman et al., 2014; Pennington-Cross & Nichols, 2000). The credit score denotes the primary constraint faced by borrowers of FHA-insured mortgages: the minimum credit score must measure at least 500 for the borrower to be eligible for such financing. Meanwhile, borrowers with a credit score from 500 and 579 must present a minimum down payment of 10% (i.e., LTV ratio cannot exceed 90%) (*Mortgage Credit Analysis for Mortgage Insurance on One- to Four-Unit Mortgage Loans (4155.1) | HUD.Gov / U.S. Department of Housing and Urban Development (HUD)*, n.d.).

Additionally, the FHA sets limits on the maximum loan amount extended to the properties underlying FHA-insured mortgages (Goodman & Nichols, 1997). These limits vary by geography and the size of the property; the county represents the smallest geography for which the loan limit is computed. The maximum loan limit for a particular geography equates to 115 percent of the area's median home price. For example, in 2021, the loan limit measured $356,362 for single-family (i.e., one-unit) properties in McLennan County, but $416,300 in Travis County (*FHA Mortgage Limits*, n.d.).

Characteristics of Borrowers

The FHA predominantly insures home purchase mortgages for first-time buyers, who comprised 83.1% of such mortgages in FY 2020, an all-time high for the FHA. The average age of first-time homebuyers has also increased, measuring 37.3 years in FY 2020, a near-four percentage point increase since 2000 (*Annual Report to Congress on the Financial Status of the MMI Fund | HUD.Gov / U.S. Department of Housing and Urban Development (HUD)*, n.d.). Due to the predominance of first-time buyers, households with FHA-insured mortgages tend to be of lower income, wealth, and credit than repeat buyers, who are generally older and therefore have acquired greater wealth (particularly through prior homeownership) and reached or achieved peak earnings (given that these borrowers have matured through the labor market) (Bhutta et al., 2017a; LaCour-Little, 2007; Pennington-Cross & Nichols, 2000).

The FHA also extends a considerable proportion of its purchase mortgages to minority households; in 2020, minority (Hispanic or Latino, non-White) households comprised nearly one-third (32.6%) of such originations: Hispanic or Latino borrowers, 17.3%; Black borrowers, 12.7%; Asian borrowers, 2.2%; and American Indian borrowers, 0.4%. Meanwhile, non-Hispanic or Latino white borrowers represented 50.1% of FHA-insured mortgages, a figure that measures below the population of non-Hispanic or Latino households in the United States (62.8%) (*Annual Report to Congress on the Financial Status of the MMI Fund | HUD.Gov / U.S. Department of Housing and Urban Development (HUD)*, n.d.). (The race and ethnicity of 17.3% of borrowers of FHA-insured mortgages was not reported.) In other words, minority households constitute a disproportionately high share of borrowers of FHA-insured mortgages (McCargo & Choi, 2020).

The average credit score of borrowers continued to decline after reaching a new peak in the wake of the Great Recession. In FY 2020, the average borrower credit score for forward purchase mortgages measured 673, a drop from the average score of 700 in FY 2011, but still-elevated in relation to average scores observed in the immediate run-up to the recession (for example, 644 in FY 2006). The vast majority of borrowers (70%) of FHA-insured mortgages depicted credit scores of less than 700. The credit score of one-third of such borrowers measured less than or equal to 680. Meanwhile, over the past two decades, the average DTI ratio for FHA-endorsed forward purchase mortgages increased considerably—nearly six percentage points from 37.6% in FY 2000 to 43.1% in FY 2020. The vast majority of FHA-insured mortgages (79%) depicted a DTI ratio of 35% or greater in 2017 (*Annual Report to Congress on the Financial Status of the MMI Fund | HUD.Gov / U.S. Department of Housing and Urban Development (HUD)*, n.d.)

Characteristics of Loans

In FY 2020, the average LTV ratio of forward purchase mortgages measured 95.6% (this figure does not reflect Mortgage Insurance Premiums financed into the loan amount). The low wealth of FHA borrowers reveals itself not only through the high average LTV ratio, but also through the proportion of borrowers with less than two months in cash reserves. In FY 2020, this figure amounted to nearly one-half (44.6%) of forward purchase mortgages (*Annual Report to*

Congress on the Financial Status of the MMI Fund | HUD.Gov / U.S. Department of Housing and Urban Development (HUD), n.d.).

VA-Guaranteed Mortgages

For nearly eight decades, VA-guaranteed mortgages have provided a path for homeownership for Servicemembers, Veterans, Reservists, National Guard members, and surviving spouses (Foote, 2010b; Spitzer & Lambie-Hanson, 2020). Although the aforementioned individuals comprise a select population, the loan guaranty program nonetheless proves quite popular among eligible borrowers and represents the second most prominent type of federally-backed mortgage—since 1944, the VA has backed over 25 million loans (*VA Guarantees More than 1 Million Home Loans in Record Year*, n.d.). Since 2005, the share of VA-guaranteed mortgages has ranged from approximately 13 percent (in 2009, during the Great Recession) to nearly 28 percent in 2017 (McCarty et al., 2019). The 2010 National Survey of Veterans indicated that two-thirds of veterans had used the VA loan guaranty program to purchase at least one home (Helmick, 2010; Spitzer & Lambie-Hanson, 2020). In 2017, the number of such mortgages tripled the number originated in 2005, largely the result of increased marketing and education and improvements to loan automation (McCarty et al., 2019). Meanwhile, in fiscal year 2020, the VA guaranteed the single highest number of loans in its history: over 1.2 million (*Annual Benefits Report - Veterans Benefits Administration Reports*, n.d.).

The federal government created the VA loan guarantee program in 1944 to counter the trade-offs made by veterans during military service, namely foregoing opportunities to accrue wealth and credit (Fischer & Rugh, 2018). In recognition of the greater difficulty faced by veterans returning from World War II in qualifying for mortgage financing, the VA loan program relaxed borrowing constraints for eligible borrowers, enhancing access to homeownership (Ricks, 2021; Wendt, 2020). VA-guaranteed mortgages offer several advantages to applicants (Foote, 2010b):

1) No down payment (provided the sales price does not exceed the appraised value of the property)
2) More favorable loan terms and interest rates than other mortgage products (interest rates competitive with those charged for conventional mortgages)
3) No requirement for private mortgage insurance (which is generally required for loans with a down payment that measures below 20%) or a mortgage insurance premium (such as is required with FHA loans)
4) Reduced closing costs, and
5) No prepayment penalty fee (i.e., the borrower can repay the mortgage early with no financial cost).

As VA-guaranteed mortgages do not require a down payment or monthly mortgage insurance, to reduce the financial burden incurred by U.S. taxpayers from these mortgages, certain borrowers must pay the one-time VA funding fee, which presently ranges from 1.4 to 3.6 percent of the sales price. For a $200,000 home, this translates into a fee between $2,800 and $7,200. (The exact percentage depends on the down payment and whether the borrower is a first-time or repeat user of VA-guaranteed mortgages.) However, as opposed to paying this fee in full at closing, borrowers may choose to finance this fee into the loan amount. Combined with the lack of a requirement for a down payment, the LTV ratio for the vast majority of VA loans exceeds 100 percent. Moreover, certain borrowers (such as those with service-related disabilities) are not required to pay the funding fee. An estimated one-third of borrowers with VA-guaranteed mortgages do not pay the fee (Goodman et al., 2014; *VA Funding Fee and Loan Closing Costs*, 2020).

Eligibility Requirements

VA-guaranteed mortgages entail several eligibility requirements. Firstly, only a small subset of households in the U.S. (19.2 million, or 5.9% of the total population) (Selleck et al., 2021) are eligible for such mortgages, including veterans, individuals on active duty, members of the National Guard or Selected Reserve, and select surviving spouses of veterans. Criteria regarding the length, character, and dates of service further qualify eligibility. As only a small portion of the national population meets such eligibility requirements, this substantially diminishes the number of households who can qualify for a VA-guaranteed mortgage. Applicants must also meet particular standards, including credit and income standards, required by the VA and private lenders (*Eligibility Requirements for VA Home Loan Programs*, 2020; Fischer & Rugh, 2018; Foote, 2010b; Goodman et al., 2014; McCarty et al., 2019; Perl, 2017; Spitzer & Lambie-Hanson, 2020).

VA-guaranteed mortgages require that the residence serve as the borrower's primary occupancy—the VA will not guarantee a home purchase loan for a second residence, such as a vacation home (*Lenders Handbook - VA Pamphlet 26-7 - Web Automated Reference Material System*, n.d.). The VA also imposes maximum loan amounts for each county in the U.S.—households with VA-guaranteed mortgages cannot borrow more than the maximum loan amount, which is $417,000 for most counties. However, such limits do not apply to eligible borrowers with full entitlement. Moreover, the maximum loan amount measures higher in counties in more costly areas, such as big cities. The VA does not impose a maximum threshold on the borrower's DTI ratio nor a minimum requirement for the credit score, but borrowers must provide compensating factors (*VA Home Loan Limits | Veterans Affairs*, n.d.).

Residual Income Test

Lenders who originate federally-backed mortgages consider similar factors in evaluating the creditworthiness of potential borrowers—as previously discussed, lenders pay particular attention to the applicant's DTI and LTV ratios and credit scores. However, the VA also encourages lenders to consider the applicant's residual income, which is "determined by subtracting taxes, the proposed shelter cost, and other obligations from the veteran's monthly income" (Foote, 2010b, p. 5). The VA publishes annual figures for the residual income, which vary based on loan size, family size, and geography (northeast, Midwest, south, and west). For example, for a family of 4, the minimum residual income for applicants with a loan amount which meets or exceeds $80,000 measures $1,025 for households in the northeast, $1,003 for households in the Midwest and south, and $1,117 for households in the west (*Lenders Handbook - VA Pamphlet 26-7 - Web Automated Reference Material System*, n.d.).

To facilitate comparisons of a particular applicant's residual income, the VA publishes minimal residual incomes as a guideline for lenders. However, these values are not intended to act as thresholds. The VA encourages lenders to evaluate the applicant holistically—i.e., to consider the applicant's residual income along with his/her borrowing constraints and housing history, as opposed to automatically rejecting or accepting an applicant based on his/her residual income (*Lenders Handbook - VA Pamphlet 26-7 - Web Automated Reference Material System*, n.d.). The loans of applicants with a residual income which does not either meet or exceed the minimal residual income for that geography may certainly be rejected, but for those on the margin (i.e., those with residual incomes below, albeit closely proximate to, the minimum residual income), the VA encourages lenders to consider the applicant's housing costs relative to the geography and the number of dependents (Foote, 2010b; Goodman et al., 2014; Jewkes & Delgadillo, 2010).

Characteristics of Borrowers

First-time homebuyers comprise a substantial portion of borrowers with VA-guaranteed mortgages. In 2019, first-time buyers represented 42% of the 384,497 purchase mortgage originations. The average income of borrowers who obtain VA-guaranteed mortgages measured $90,156 (while the median income measured $78,864). Meanwhile, the median assets of such borrowers slightly exceeded $10,000. The credit score for the majority of borrowers (56%) with VA-guaranteed mortgages measured or exceeded 700. Only 12% of borrowers reported a credit score of less than 640. The vast majority of VA-guaranteed mortgages (71%) depicted a DTI ratio of 35% or greater in 2017 (*Annual Benefits Report - Veterans Benefits Administration Reports*, n.d.).

Non-Hispanic or Latino whites continued to comprise the vast majority of borrowers with VA-guaranteed mortgages, representing nearly two-thirds (65.6%) of such borrowers in 2019. Black or African American households constituted the second highest proportion of borrowers

(12.3%), followed by American Indian or Alaska Native households (10.4%), Hispanic or Latino households (8.5%), and, finally, Asian, Pacific Islander, or Native Hawaiian households (3.1%). Males comprised a considerably higher proportion of borrowers with VA-guaranteed mortgages (87.9%) (*Annual Benefits Report - Veterans Benefits Administration Reports*, n.d.).

The age distribution of VA-guaranteed loans varies, but generally speaking, as the borrower's age increases, the proportion of loans guaranteed decreases (with the exception of borrowers under the age of 26, who comprised a mere 4.5% of all borrowers in 2019). Borrowers who are 26-45 years old continued to constitute the largest swath of borrowers—nearly one-half (45.6%) of all borrowers. The income distribution of VA-guaranteed loans skews to the left; over one-half (54.2%) of borrowers reported incomes greater than $75,000. A mere 3% of borrowers earned less than $35,000, while nearly one-fifth (18%) earned between $35,000 and $54,999 (*Annual Benefits Report - Veterans Benefits Administration Reports*, n.d.).

Characteristics of Loans

In fiscal year 2019, the average loan amount for the 384,497 VA-guaranteed home purchase mortgages measured $277,837. Meanwhile, the average guaranty amount equaled $68,418, or 24.6%. As previously mentioned, since the VA loan guaranty program does not mandate a downpayment and allows particular borrowers to finance the up-front fee into the loan amount, the LTV ratio for the majority of borrowers of VA-guaranteed mortgages exceeds 100%. Meanwhile, in 2019, approximately 80% of borrowers of VA-guaranteed mortgages did not provide a down payment (*Annual Benefits Report - Veterans Benefits Administration Reports*, n.d.).

The average loan amount varied considerably by the race and ethnicity of the borrower in 2019. It measured as high as $342,794 for Asian/Pacific Islander/Native Hawaiian borrowers, and as low as $275,411 for Black/African American borrowers. The average loan amount differed only slightly between males and females ($281,707 vs. $277,738), but more considerably between first-time and repeat buyers: $248,444 versus $299,050. Similarly, the average loan amount for borrowers with a down payment ($347,471) exceeded that of borrowers without a down payment ($260,225). Naturally, the average loan amount increases as the borrower's income increases. The amount ranged from $97,561 for borrowers who earned less than $25,000 and $339,639 for borrowers who earned $75,000 or more (*Annual Benefits Report - Veterans Benefits Administration Reports*, n.d.).

RHS-Guaranteed Mortgages

The Section 502 Guaranteed Rural Housing Loan Program, an entity of the Rural Housing Service (RHS) of the U.S. Department of Agriculture (USDA), represents the third most prominent type of federally-backed mortgage, yet comprises a very small proportion of mortgage loans nationwide. In 2019, RHS-guaranteed mortgages constituted less than 5% of all home purchase mortgage originations for single-family, owner-occupied properties (*HMDA Data Publication*, n.d.). However, since the 1990s, the number of RHS-guaranteed mortgages originated each year has increased considerably, from approximately 20,000 such mortgages in 1996 to over 150,000 mortgages in 2013 (Foote, 2010a; Scally & Lipsetz, 2017).

RHS-guaranteed mortgages serve low- and moderate-income households that construct new or purchase existing homes in eligible rural communities, which tend to be underserved by private lenders. Most borrowers earn between 80 and 115 percent of area median income, although the program may extend mortgages to qualifying households that earn less than 80 percent of area median income (Foote, 2010a; Scally & Lipsetz, 2017). (As of January 2004, around 30 percent of RHS-guaranteed loans were originated to households with incomes below 80 percent of area median income.) RHS-guaranteed mortgages pose several benefits to applicants, including the lack of a downpayment or cash reserves. Furthermore, as the program will lend up to 100% of the appraised value of the property, borrowers may be able to finance closing costs and home repair expenses into the loan amount (*Single Family Housing Guaranteed Loan Program | Rural Development*, n.d.).

Eligibility Requirements

RHS-guaranteed mortgages entail several eligibility requirements, which significantly diminish the number of households who can qualify for such mortgages. Applicants must meet several requirements (*Single Family Housing Guaranteed Loan Program | Rural Development*, n.d.):

1) Applicants must submit a one-year history of income. (The program mandates a two-year history for self-employed or seasonal applicants.)
2) Furthermore, the household income of applicants cannot surpass 115% of median household income.
3) Applicants must agree that the RHS-guaranteed property will serve as the primary residence for the duration of the mortgage.
4) Applicants must be a U.S. citizen, U.S. non-citizen national, or Qualified Alien.

5) Applicants must be unable to qualify for conventional mortgage financing without private mortgage insurance.
6) Applicants must be allowed to participate in federal programs.
7) While the program does not stipulate a particular credit score, applicants must exhibit creditworthiness.
8) The front-end DTI ratio generally cannot exceed 29% of gross monthly income. The front-end DTI ratio relates the total housing payment—mortgage principal and interest, property taxes and insurance, HOA dues, and the annual fee—to household income. Moreover, the back-end DTI ratio generally cannot exceed 41% of gross monthly income. The back-end DTI relates the household's total debt payments—the total housing payment in addition to credit card and car loan payments—to household income.

Properties must meet the following requirements (*Single Family Housing Guaranteed Loan Program | Rural Development*, n.d.):

1) Households must purchase a home in an eligible rural area, the definition of which proves quite convoluted. Overarchingly, the properties of applicants seeking RHS-guaranteed mortgages must be located in communities of 35,000 people or less.
2) The property must meet the minimum building standards stipulated by HUD and must be a single-family dwelling.

Characteristics of Borrowers

From fiscal years 2010-2014, the median income of borrowers with single-family home purchase RHS-guaranteed mortgages measured $44,000, considerably less than that of comparable FHA mortgages ($57,000). However, FHA and RHS borrowers depicted similar median credit scores and front-end DTI ratios—685 and 23-24, respectively. (The front-end DTI ratio solely reflects housing expenses—i.e., mortgage principal and interest and property taxes and insurance—as opposed to all debts borne by the household, such as credit card and student loan debt, as measured by the back-end DTI ratio). The LTV ratio of RHS-guaranteed mortgages exceeded 100%—the median value measured 101%, largely a phenomenon of the no down payment requirement of RHS-guaranteed mortgages and the ability of borrowers to finance the guarantee fee into the loan amount (*Home Mortgage Guarantees*, n.d.).

Neighborhood Characteristics

For an FHA-insured, VA-guaranteed, and RHS-guaranteed mortgage, neighborhood characteristics may affect the applicant's ability to purchase the home in question. The appraisal, conducted in the latter stages of the home purchasing process, after the loan applicant choses the particular home he/she wishes to purchase but prior to closing, considers the characteristics of the neighborhood for the particular home in question. In essence, the appraisal is an assessment of the value of the home—i.e., its fair market value. The appraiser computes this estimated value by inspecting the property, considering its location, and comparing it to homes recently sold in the surrounding area (Howell & Korver-Glenn, 2018; Lentz & Wang, 1998). FHA-insured, VA-guaranteed, and RHS-guaranteed mortgages require the Uniform Residential Appraisal Report (URAR). The appraisal report indicates that, by and large, obtaining a mortgage loan for a particular home depends—at least partially—on the economic conditions of the neighborhood. The overarching emphasis of the "Neighborhood" section rests on articulating the economic conditions of the neighborhood surrounding the property (*Mortgage Credit Analysis for Mortgage Insurance on One- to Four-Unit Mortgage Loans (4155.1) | HUD.Gov / U.S. Department of Housing and Urban Development (HUD)*, n.d.).

The first point of consideration in discussing the neighborhood characteristics weighed by the URAR lies in defining "neighborhood." The report requests the "Neighborhood Name," which represents the "the name of the subdivision, if applicable, or the commonly known local neighborhood designation. If the subject property is in a PUD, provide the name of the development." As the first sentence suggests, there is a degree of ambiguity in defining the neighborhood (as observed in the phrase "the commonly known local neighborhood designation"). The second point of consideration in reviewing the "Neighborhood" section of the URAR rests on a note at the top of the section: "Race and the racial composition of the neighborhood are not appraisal factors" (*Mortgage Credit Analysis for Mortgage Insurance on One- to Four-Unit Mortgage Loans (4155.1) | HUD.Gov / U.S. Department of Housing and Urban Development (HUD)*, n.d.).

The "Neighborhood" section of the URAR contains several categories—1) neighborhood characteristics, 2) one-unit housing trends, 3) one-unit housing, and 4) present land use—in addition to free-response sections for the neighborhood boundaries, neighborhood description, and market conditions. With respect to the first category, the appraiser selects among three options for the location (urban, suburban, or rural), among three options for the "built-up," or the percentage of available land within the neighborhood that has been developed (over 75%, 25-75%, or under 25%), and among three options for the growth rate of the neighborhood (rapid, stable, or slow) (*Mortgage Credit Analysis for Mortgage Insurance on One- to Four-Unit*

Mortgage Loans (4155.1) | HUD.Gov / U.S. Department of Housing and Urban Development (HUD), n.d.).

For the second category (one-unit housing trends), the appraiser considers the value for one-unit homes in the surrounding neighborhood (increasing, stable, or declining) based on trends in the values of recently sold and resold homes, weighing any improvements made in the intermediary duration. The appraiser also reviews the demand/supply by considering the proportion of homes recently sold to those listed (but not sold)—shortage, in balance, or over supply. Finally, the appraiser denotes the marketing time (under 3 months, 3-6 months, over 6 months), based on the average duration a property comparable to the subject property would spend on the market. As for the third category (one-unit housing), the appraiser enters the low, high, and predominant prices and age of homes within the neighborhood. With respect to the fourth category (present land use %), the appraiser records the proportion of one-unit, two-to-four-unit, multi-family, commercial, and properties with land use designated as “other” in the neighborhood (*Mortgage Credit Analysis for Mortgage Insurance on One- to Four-Unit Mortgage Loans (4155.1) | HUD.Gov / U.S. Department of Housing and Urban Development (HUD)*, n.d.).

CHAPTER III

LITERATURE REVIEW

"There is a continuing high level of interest in measuring the affordability of the stock of owner-occupied houses in the U.S." (Haurin, 2016, p. 3)

"'If poverty is a disease that infects an entire community in the form of unemployment and violence, failing schools and broken homes, then we can't just treat those symptoms in isolation. We have to heal the entire community. And we have to focus on what actually works.'" -Barack Obama, July 18, 2007 (Whitehurst, 2010, p. 1)

Housing affordability, generally perceived to denote the relationship between household income and housing costs, presently proves one of the most persistent and pervasive problems facing housing planners and policymakers—both with respect to owner- and renter-occupied housing (Dokko, 2018; S. Gabriel & Painter, 2018; Rohe, 2017; Wetzstein, 2017). Affordability emerged as the primary objective of federal housing policy nearly one century ago, during the administration of President Franklin Delano Roosevelt, who famously declared in his second inaugural address (1937): "I see one-third of a nation ill-housed…" (Sawhill et al., 2016, p. 3). By creating the secondary mortgage market, which reduced the risk posed by borrowers on financial institutions and thereby incentivized lenders to extend loans to borrowers historically unable to access mortgage credit, the Roosevelt administration particularly facilitated purchase affordability—that is, the ability of households to access mortgage credit and therefore attain homeownership (Jones et al., 2017; Schwartz, 2021).

Although housing affordability—particularly purchase affordability—emerged as perhaps the primary prerogative of federal housing policy in the 1930s, it received renewed interest under the administrations of Presidents Clinton and George W. Bush in the 1990s and 2000s (Beracha & Johnson, 2012). Both administrations, which framed homeownership as a vital component of the American Dream, sought to increase access to homeownership, especially among traditionally underserved households (low-income and minority households). The national homeownership rate peaked at over 69% in 2004 (Gabriel, 2003; Gabriel & Rosenthal, 2005). However, over the past decade plus, several factors have diminished purchase affordability (Amromin et al., 2020; Fazzari & Needler, 2021; Rohe, 2017; Torres, 2017):

1) The Great Recession, which induced large losses in income, particularly among low-income and minority households,
2) The continued stagnation of wages and income with respect to housing costs,
3) Shortages of land, labor, and materials, which suppress the supply of housing and increasing the costs of construction, and
4) The COVID-19 Recession, which, akin to the Great Recession, heavily disrupted the nation’s labor market, leading to massive losses in income, but especially among low-income and minority households.

While it would be quite ideal to be able to offer a single statistic to summarize the past and present states of housing affordability (under the auspices of augmenting the rationale for studying affordability), herein lies the crux of the problem of affordability itself. Significant conceptual and methodological limitations enshroud the term, obfuscating one's ability to even definitively declare the presence of a housing affordability problem (Dokko, 2018). Nonetheless, talk of a "housing affordability crisis" currently runs rampant, leading one scholar to conclude: "The United States is experiencing a housing crisis unlike anything we have seen for decades….This housing affordability crisis is exacting great costs both from individuals and from society" (Rohe, 2017, p. 490).

Although scholars, practitioners, and policymakers continue to debate the validity of the perceived affordability problem, its considerable clout in planning and policymaking circles dictates a deeper dive into its connotations, applications, and implications (Quigley & Raphael, 2004). Moreover, in the wake of the significant layoffs and reduced hours stirred by COVID-19 Recession, continued and significant declines in household income across the U.S., but particularly for low-income and minority households, enhance the importance of developing a more comprehensive understanding of housing affordability (Amromin et al., 2020; Spatt, 2020). With respect to purchase affordability specifically, as homeownership remains deeply embedded in federal housing policy, understanding the home purchasing potential of households will continue to prove crucial to federal policymakers, particularly those who determine mortgage credit availability, as well as state and local planners, who dispense federal funds for housing assistance, determine land use planning, etc. (Dokko, 2018; Fishback et al., 2001; Jones et al., 2017; McCarty et al., 2019).

The "geography of opportunity," a la "neighborhood opportunity," "neighborhoods of opportunity," etc., predominates present-day planning—particularly in the realm of fair housing and community development—and even emerged as the subject of significant policy attention in a past presidential administration (that of President Obama, himself a former community organizer) (Lens, 2017; Patterson et al., 2015). In short, the geography of opportunity describes the numerous and varied effects of neighborhoods on the individuals and households that inhabit them. It posits that the attributes of neighborhoods (i.e., institutions, resources, amenities, etc.) indelibly impact individuals' lives (Chetty et al., 2014; Galster & Killen, 1995).

Neighborhoods are not created equally; as such, opportunity exists on a spectrum. High-opportunity neighborhoods house the highest quality schools, jobs, daycares, medical facilities, etc; higher-income households disproportionately inhabit such neighborhoods. Meanwhile, lower-income households are intentionally sequestered into less desirable, or "low-opportunity" neighborhoods, effectively ensuring reduced socioeconomic outcomes through greater exposure to negative externalities such as poverty, crime and delinquency, deleterious health effects, and psychological distress (Bergman et al., 2019; Lens & Reina, 2016). Disparate access to higher-opportunity neighborhoods exacerbates pre-existing racial and economic inequalities (Ellen & Turner, 1997; Shelby, 2017).

Public policy—housing policy in particular—bears a long legacy of practices and programs which have shaped the trajectory of both individuals and neighborhoods—in either case, particularly and most perniciously along the lines of race and class (Gotham, 2000; Hirsch, 2000; Landis & McClure, 2010). The geography of opportunity visibly undergirds the rationale for a vast number of *recent* policy interventions promulgated by federal, state, and local governments, of which the residential mobility programs perhaps prove the most notable (Silverman et al., 2017). Initially, people-based policies—such as residential mobility programs

(Gautreaux, Moving to Opportunity, and the Baltimore Residential Mobility Program)—predominated, but a significant shift occurred during the Obama administration, which favored place-based policies (Choice and Promise Neighborhoods) and continued (purportedly) during the subsequent Trump administration (via Opportunity Zones) (DeLuca & Rosenblatt, 2017; Eastman & Kaeding, 2019; Gelfond & Looney, 2018; Lens & Reina, 2016).

Although "opportunity"—as in "neighborhood opportunity"—is certainly common parlance in present-day discussions on place, the term remains enshrouded in a number of conceptual and methodological limitations which diminish its utility and effectiveness in its applications to policy (Goetz, 2017; Knaap, 2017). Contention over the correct variables to use in metrics of neighborhood opportunity, as well as concerns over the normative standards imposed by the concept of neighborhood opportunity, rank among the most significant of these limitations. The discussion of these issues generally stems from the decades-old debate over people- vs. place-based housing: in essence, the perceived merits of relocating households from low-opportunity to high-opportunity neighborhoods vs. revitalizing low-opportunity neighborhoods (Davidson, 2009; G. Galster, 2017a; Turner, 2017).

This chapter consists of two sections: 1) indicators of owner-occupied housing affordability and 2) neighborhood opportunity. The first section provides an overview of the popularly-promulgated definitions of housing affordability and the conceptual limitations which enshroud them. Notably, although this research focuses specifically on purchase affordability, most definitions of housing affordability provide only a general overview of the concept, and do not parse owner- from renter-occupied housing affordability, nor purchase from repayment affordability. As such, it is difficult to provide definitions tailored to purchase affordability. This chapter will also discuss the most common indicators of owner-occupied housing affordability and the methodological limitations embedded in them. This section concludes with suggestions for a new indicator of purchase affordability.

The second section of this chapter provides an overview of the geography of opportunity, including its origins and a brief history of its application to federal housing policy. It also reviews people- vs. place-based housing policy and the limitations of each approach. Finally, it discusses the practice of opportunity mapping, with particular attention devoted to the methodology and limitations of each.

Definitions of Housing Affordability

The literature offers no consistent formal definition of housing affordability: as Linneman and Megbolugbe succinctly stated in an oft-cited line, "Talk of housing affordability is plentiful, but a precise definition of housing affordability is at best ambiguous" (Linneman & Megbolugbe, 1992, p. 371). Bourassa reached a similar conclusion: "[housing] affordability is a very slippery thing to try to grasp" (Bourassa, 1996, p. 1870). Indeed, Wilcox deemed the concept a "vexed" one (Wilcox, 1999). "It means different things to different people" (Haffner & Heylen, 2011, p. 593).

In framing the discussion on definitions of housing affordability, it is imperative to parse owner- from renter-occupied affordability, and for owner-occupied affordability, purchase from repayment affordability. The focus of this dissertation rests specifically on purchase affordability, which concerns the ability of a household (whether a current renter or owner) to attain homeownership. It generally attracts more attention from policymakers and the public at large, namely the phenomenon of the policy emphasis of the federal government on promoting homeownership (Carliner, 1998; McCarty et al., 2019). Conversely, repayment affordability concerns the ability of preexisting borrowers to make timely mortgage payments and therefore repay the remaining loan balance (Gan & Hill, 2009).

Developing a clear definition of housing affordability—or at least understanding its myriad interpretations—cannot be emphasized enough. Indicators of housing affordability have been used to direct planning and policy decisions on the provision of affordable housing and the allocation of housing assistance (Gabriel & Painter, 2018; Kutty, 2005). When loosely-defined (and therefore subject to a variety of interpretations and adaptations), one, at the very least, would question the soundness of any conclusions or decisions derived from the concept: “The literature on housing affordability provides multiple answers, with the level of consensus decreasing the greater the level of detail provided in the definition” (Haurin, 2016, p. 4).

Over the three decades that span the literature on housing affordability, scholars have proposed numerous definitions of the term, which depict a wide range in specificity. These definitions apply broadly to both owner- and renter-occupied housing affordability, and are not specific to purchase affordability, despite the differences among definitions (Stone, 2006). It is apparent that the definitions promulgated in the academic literature are primarily concerned with specifying a level of housing consumption appropriate for a given income threshold; in other words, the definitions frame “affordability” as the relationship between housing costs and household income:

- “to pay housing expenses and still have enough for nonhousing necessities” (Lerman & Reeder, 1987, p. 389)
- “Housing is not affordable for a household if it excessively crowds out other expenditure” (Thalmann, 2003, p. 294)
- “Affordability is concerned with securing some given standard of housing (or different standards) at a price or rent which does not impose, in the eye of some third party (usually government) an unreasonable burden on household incomes” (Hancock, 1993, p. 129)
- “it is an expression of the social and material experiences of people, constituted as households, in relation to their individual housing situations. Affordability expresses the challenge each household faces in balancing the cost of its actual or potential housing, on the one hand, and its nonhousing expenditures, on the other, within the constraints of its income” (Stone, 2006, p. 151)
- “what has to be foregone in order to obtain housing” (Hancock, 1993, p. 129)
- “only those households who given their income and the cost of their housing, could not potentially consumer the required level of housing without breaking the affordability criteria are regarded as having a [affordability] problem” (Whitehead, 1991, p. 875)
- “Affordability is a relative concept, a relationship between what a consumer can afford and what the product or service costs” (Hartman, 2008, p. 250)
- “Opportunity ‘cost’ in relation to expenses in terms of what has to be foregone can be regarded as using current household income for housing consumption instead of other consumption (or saving)” (Haffner & Heylen, 2011, p. 595)

Governmental agencies, the real estate industry, non-profits, and other organizations have also developed distinct interpretations of housing affordability. These definitions are likewise concerned with the relationship between housing costs and household income:

- “Housing practitioners generally agree that housing is ‘affordable’ if the tenants pay no more than 30 percent of their household income toward housing costs” (Joice, 2014, p. 301)
- “an affordability index should measure the full cost of housing faced by the homeowner” (Haurin, 2016, p. 1)
- “affordability should be defined in terms of the adequacy for other household needs of income remaining after deducting housing costs” (Bourassa, 1996, p. 1869)

Other scholars argue that affordability should not be narrowed to one exact definition: “affordability is not a one-dimensional concept, and a combination of more than one concept will give better insight into the affordability of housing for consumers” (Haffner & Heylen, 2011, p. 594). Despite the lack of a consistent definition of housing affordability (or perhaps as a result of it), existing indicators, or measures, of housing affordability broadly establish, using household income and housing costs, an arbitrary standard above which housing is considered unaffordable (Quigley & Raphael, 2004). Indicators of housing affordability are ubiquitous in housing circles, applied by the public, private, and nonprofit sectors alike to guide policy and real estate development and investment decisions and advocate for the increased supply of affordable housing (Dokko, 2018; Joice, 2014; O’Dell et al., 2004).

Conceptual Limitations

Although a particularly popular topic at present, several conceptual limitations continue to plague definitions of housing affordability (Stone, 2006). Such limitations pose several concerns for planning practitioners and policymakers, who may face difficultly in 1) proving the existence of a perceived affordability problem, 2) defining the scope of the problem, and 3) seeking sufficient assistance to address the problem (Dokko, 2018). The myriad of limitations stem from the variety of distinct topics which are contained under the singular subject of affordability: “Economists are wary, even uncomfortable, with the rhetoric of “affordability,” which jumbles together in a single term a number of disparate issues: the distribution of housing prices, the distribution of housing quality, the distribution of income, the ability of households to borrow, public policies affecting housing markets, conditions affecting the supply of new or refurbished housing, and the choices that people make about how much housing to consume relative to other goods.” (Quigley & Raphael, 2004, p. 192). It is important to note that the criticisms which encapsulate definitions of housing affordability bleed into the criticism of indicators of affordability.

Positioning affordability solely as a function of household income and housing costs (and, in some instances, a minimum standard of housing) fails to encapsulate the broad array of additional factors which affect housing affordability, including household size and composition, characteristics of the neighborhood (including locational access to amenities and resources), and the age of the head(s) of household (Fisher et al., 2009; Jewkes & Delgadillo, 2010; Lerman & Reeder, 1987; O’Dell et al., 2004). Moreover, regardless of socioeconomic inequalities, the definitions also fail to account for heterogeneity in behaviors exhibited across the income distribution (Gan & Hill, 2009). The two most widely-vocalized criticisms of current definitions of housing affordability stem from the lack of theoretical underpinnings present in existing definitions and encapsulate the poor rationale currently proffered as proof of an affordability problem:

1) Endogeneity, which posits that households select housing costs based on their tastes and preferences (i.e., individual households decide how much housing to consume relative to their budget constraint—i.e., income) (Dokko, 2018; Thalmann, 2003).
2) The normative standard established by such definitions, which encourages users to impose arbitrarily thresholds above which housing is declared unaffordable (Linneman & Megbolugbe, 1992).

Endogeneity

Economists, ever wary of equating issues endemic to the labor market (i.e., wages and income) to issues endemic to the housing market (i.e., housing costs), pose considerable concern as to the endogeneity present in both conceptual and therefore methodological frameworks of housing affordability (Dokko, 2018; Hancock, 1993). Neoclassical economic theory generally dictates that each individual household defines that which is affordable to them. In other words, each household sets budget constraints according to its tastes and preferences, the opportunity costs embedded in housing consumption, etc., so as to maximize its own utility. The budget constraint determines the household’s optimal threshold to devote to housing costs. In other words, the affordability problem is imagined in the sense that households themselves decide how much housing is affordable to them (Quigley & Raphael, 2004; Bourassa, 1996). Most economists argue that proving the presence of an affordability problem requires aligning individuals' budget constraints with the price of housing (Hancock, 1993; Thalmann, 1999). In actuality, estimating those constraints begets a laborious and fruitless practice for planning practitioners and policymakers. Therefore, such protestations of the dubious nature of the term "housing affordability" are undoubtedly difficult to disprove, but necessary to consider in the broader context of defining affordability.

The primary challenge associated with the endogeneity observed in housing affordability rests on the inability of scholars and practitioners to readily observe and/or parse factors outside of the control of the household—i.e., exogenous factors, such as land use planning decisions—from those made by individual households—i.e., households select budget constraints, tastes and preferences, etc. Distinguishing the former from the latter proves a particularly convoluted task. As such, most indicators of housing affordability face the trade-off of ease of application and interpretation vs. capturing household's budget constraints. To be certain, higher-income households select housing according to their tastes and preferences. However, lower-income households, which grapple with significantly lower budget constraints, will likely face much more difficulty in being able to procure housing—particularly decent, safe, and sanitary housing (i.e., the minimum standards imposed by the government) within the confines of said budget constraint (Galster & Lee, 2020; Gan & Hill, 2009; Lerman & Reeder, 1987).

Normative Standards

The dubious theoretical foundations which undergird definitions of housing affordability diminish the rationale for government intervention in the housing market to ease perceived affordability problems. Support for public policy generally requires strong rationale; however, existing definitions of affordability do not promulgate such a rationale, but rather tautological or arbitrary standards by which to measure affordability (Dokko, 2018; Stone, 2006). In essence, the dependence on normativity exhibited by the definitions diminishes the rationale for public policy interventions. The arbitrary thresholds facilitated in definitions of "affordability" lend issue to the arbitrary delineation between housing which is "affordable" and that which is "unaffordable." In essence, the definitions encourage users to consider affordability as a dichotomous variable; i.e., housing is either "affordable" or "unaffordable"—affordability cannot exist along a spectrum under such an assumption (Gan & Hill, 2009; Hancock, 1993; Thalmann, 2003). Defining the precise moment at which housing costs which were once "affordable" then become "unaffordable" proves dubious at best.

Indicators of Owner-Occupied Housing Affordability

As planners, policymakers, and practitioners consistently express housing affordability to be an issue of considerable concern, quantifying owner-occupied housing affordability—particularly, the methodology of popular indicators—remains a particularly salient topic (Joice, 2014). Indicators of owner-occupied housing affordability, developed from decades of research and feedback from a variety of scholars, nonprofit organizations, and trade associations, prove of critical importance in framing discussions on the presence, nature, and magnitude of perceived affordability problems and in formulating policy interventions (Dokko, 2018; Haurin, 2016). Professionals across a variety of industries, including mortgage lenders, non-profit organizations, policymakers and legislators, city council representatives, planning practitioners, and housing counseling agencies, utilize indicators of owner-occupied housing affordability (Jewkes & Delgadillo, 2010).

Although each indicator produces a slightly different interpretation of affordability, the indicators generally depict affordability as the relationship between household income and either home prices or housing costs. The three most widely promulgated include the Housing Affordability Index, developed by the National Association of Realtors, the Median Multiple (also known as the home price-to-income multiplier), and the HUD Guideline (also known as the 30% of income standard) (Bourassa & Haurin, 2017; Jewkes & Delgadillo, 2010; O'Dell et al., 2004). However, despite the myriad measures, owner-occupied housing affordability remains a much-contested topic. Existing indicators, particularly the most common indicators, present several methodological limitations which may obfuscate the interpretation and application of each indicator and therefore potentially diminish its utility to its users (Abelson, 2009; Bogdon & Can, 1997).

This section provides an overview of the indicators of housing affordability relevant to owner-occupied housing, with particular attention paid to indicators of purchase affordability. (As previously discussed, indicators of housing affordability often do not explicate owner- from renter-occupied housing, nor, in the instance of owner-occupied housing, purchase from repayment affordability.) Specifically, I review the different types, purposes, and policy implications of these indicators. The focus lies on the three aforementioned indicators widely promulgated by planning practitioners, policymakers, and scholars, but I also discuss the Housing Opportunity Index and the Dynamic Housing Affordability Index. I also assess the methodological limitations of each of these indicators and offer suggestions for future indicators.

Types of Indicators

The myriad definitions of housing affordability yield a multitude of methodological interpretations and discrepancies in the indicators themselves. Indeed, "There are many conceptualizations of how to measure housing affordability and there are many affordability indexes" (Haurin, 2016, p. 1). Differences in the intended application of the indicators—i.e., the intended user(s) and use(s)—also affects the framework upon which the indicators are founded. While there are multiple indicators of owner-occupied housing affordability, the indicators generally fall into four main categories (Bourassa & Haurin, 2017; Haurin, 2016):

1) The ratio approach, which compares home prices or housing costs to household income,
2) The residual income approach, which deducts housing expenditures from household income and compares the remaining income to a residual income standard,
3) A comparison of the current cost of an existing home to the cost of new construction (less land costs), and the
4) Owner cost/user cost theory, or the cost of owner-occupied housing per dollar of home value.

The Ratio Approach

The ratio approach represents the most simplistic—and ubiquitous—method for measuring housing affordability. It relates home prices or housing costs (either renter- or owner-occupied housing affordability) to household income. Three commonly promulgated indicators that fall under the ratio approach include the Median Multiple, HUD measure, and the Housing Affordability Index (developed by the National Association of Realtors). Closely related to the Housing Affordability Index, the Housing Opportunity Index (developed by the National Association of Home Builders) proves less ubiquitous, but still relevant to the discussion (Jewkes & Delgadillo, 2010; O'Dell et al., 2004).

The popularity of the ratio approach largely derives from the ease of its computation, comprehension, and interpretation. Users generally only need to gather a few pieces of data—namely the household's income and home price or housing costs. Median household income and home price or housing cost data prove readily accessible from a variety of sources, including the U.S. Census Bureau and HUD. Furthermore, the simplistic structure of the measure facilitates ready comparisons of values across time and geographies, including counties, MSAs, and states. Government agencies prove particularly fond of measures of housing affordability that adopt the ratio approach, as emblemized in the HUD measure, the legislative standard for determining a household's eligibility for housing assistance (Joice, 2014; O'Dell et al., 2004).

Residual Income Approach

The residual income approach compares the proportion of a household's after-tax income devoted to housing expenses to an assumed minimum amount of non-housing expenses. In other words, this approach involves 1) computing the household's after-tax income, 2) estimating the household's housing expenses, 3) deducting housing expenses from income, and 4) comparing the remaining (or residual) income to a pre-determined minimum amount of non-housing expenses (adjusted for household size and location). If the household's residual income measures above (below) the minimum threshold for non-housing expenses, housing is affordable (unaffordable). Non-housing expenses include necessary goods and services such as food, clothing, child care, and medical care (Kutty, 2005; Stone, 2006).

The residual income is compared to a bench line standard, such as poverty thresholds, to assess whether a household has sufficient income, after paying for housing, to meet its basic non-housing needs. By recognizing that higher-income households can reasonably devote a higher percentage of income to housing than lower-income households, the residual income approach should provide a more accurate estimate than the 30% of income standard of housing affordability across the income distribution (Hancock, 1993; Thalmann, 2003). The Department of Veterans Affairs (VA) adapted the residual income approach to establish qualifying criteria for mortgage loans (Goodman et al., 2014).

Construction Costs

By combining household income and home prices or housing costs, the vast majority of indicators of owner-occupied housing affordability suffer from endogeneity. That is, individuals chose how much income to devote to housing. By equating household income with home prices or housing costs, users conflate issues endemic to the labor market with issues endemic to the housing market (Dokko, 2018; Quigley & Raphael, 2004). Under such conditions, measures of affordability function simultaneously as indicators of poverty and housing. As such, measures of affordability should compare home prices or housing costs to an exogenous factor, such as construction costs: “To us, a housing affordability crisis means that housing is expensive relative to its fundamental costs of production—not that people are poor” (Glaeser & Gyourko, 2005, p. 21). In other words, replacing income with construction costs removes the issue of endogeneity, as construction costs are not determined by the decisions of individual households.

This approach purposefully poses an antithesis to the ratio and residual income approaches, for which endogeneity proves a primary concern. Although well-rooted in economic theory, the practical applications of the construction cost approach are limited: it poses difficulties in computation and comprehension. Furthermore, replacing income with construction costs changes the commonly-understood conception of affordability as one which denotes the relationship between household income and home prices or housing costs (Glaeser & Gyourko, 2005; Haurin, 2016).

User Cost Theory (Affordability as Measured by the User Cost of Housing)

User cost theory (which measures affordability by the user cost of housing) represents a significant departure from the two more popular measures of owner-occupied housing affordability (the ratio and residual income approaches). Economists, tend to favor the user cost theory, as it is derived from economic theory (Dokko, 2018; Glaeser & Gyourko, 2005;

Thalmann, 1999). The user cost theory weighs both the costs and benefits of investing in homeownership—specifically, based on the expected tenure of homeownership, user cost theory considers the costs of borrowing (i.e., the mortgage interest rate) and accompanying transaction costs involved in the purchase and sale of the property, taxes (property & income taxes), depreciation and maintenance, and home price appreciation. Although strongly rooted in economic theory, the user cost theory poses a number of limitations; chiefly, that the indicators developed from it prove particularly cumbersome for planning practitioners and policymakers, who often encounter difficulty navigating its nuances (Bourassa & Haurin, 2017).

Overview of Four Indicators of Owner-Occupied Housing Affordability

Despite the myriad indicators of purchase affordability, most remain relatively unused (or scarcely used), with the exception of four measures: the Median Multiple, HUD measure (also known as the 30% of income standard), Housing Affordability Index (HAI), and the Housing Opportunity Index (HOI). The Median Multiple, HAI, and HOI serve as measures of purchase affordability, while the HUD measure reflects repayment affordability. Although not a measure of purchase affordability, the federal government adopted the HUD measure as its “official” indicator of affordability—i.e., federal housing policy uses the HUD measure to determine a household’s eligibility for housing assistance (Joice, 2014; O’Dell et al., 2004).

This section describes the four most popular measures of owner-occupied affordability. Specifically, I discuss the methodology of each indicator and its interpretation. The section concludes with a discussion on the methodological limitations of the four indicators.

HUD Measure

The HUD measure, the legislative standard which determines a household's eligibility for housing assistance, proves the predominant measure of housing affordability, as it applies to either owner- or renter-occupied housing. The significance of the HUD measure, also known as the 30 percent of income standard, cannot be overstated: "It is often considered the definition of housing affordability…and has shaped views of who has affordability problems, the severity of problems, and the extent of the problems" (Jewkes & Delgadillo, 2010, p. 46). The HUD measure stipulates that households which spend more than 30% of gross annual income on total housing costs are cost-burdened. (For homeowners, housing costs include mortgage principal and interest, property taxes, and utilities—electricity, water, gas, and sewer, and insurance.) Households which spend more than 50% of gross annual income on total housing costs are severely housing cost burdened. The measure therefore defines affordability to be met when households spend less than 30% of annual gross income on total housing costs. The HUD measure closely corresponds to qualifying ratios (i.e., DTI ratios) utilized by mortgage lenders (Hamidi et al., 2016; Joice, 2014; O'Dell et al., 2004).

Median Multiple

The Median Multiple, or home price-to-income ratio, measures the relationship between the median home price and median annual (pre-tax) household income in a particular geography.

For example, the Median Multiple for a city with a median home price of $200,000 and median household income of $50,000 would measure 4.0 ($200,000/$50,000). Each year, Demographia circulates a report depicting the Median Multiple for major cities around the world. The organization classifies affordability on a spectrum, from “affordable” for geographies in which the Multiple measures no greater than 3.0, to “moderately unaffordable” for geographies in which the Multiple measures between 3.1 and 4.0, to “seriously unaffordable for geographies in which the Multiple measures between 4.1 and 5.0, and, finally, to “severely unaffordable” for geographies in which the Multiple is greater than 5.0 (Cox & Pavletich, n.d.).

National Association of Realtors Housing Affordability Index

The Housing Affordability Index (HAI), produced by the National Association of Realtors (NAR), a trade association, represents the most ubiquitous indicator of purchase affordability. It “measures whether or not a typical family earns enough income to qualify for a mortgage loan on a typical home at the national and regional levels based on the most recent price and income data” (*Housing Affordability Index*, n.d.). In other words, it measures the ability of a household earning the area median family income (MFI) to qualify for a mortgage loan on the median-priced, existing single-family home. The index is published on a monthly, quarterly, and annual basis for the nation and metropolitan areas. It proves of immense popularity: “The U.S. national media constantly focuses on the NAR measure and has adopted it as an acceptable measure of housing affordability….One could say that the NAR measure is the media's 'pet' housing affordability measure" (Jewkes & Delgadillo, 2010, p. 47).

The index computes the mortgage payment (principal and interest) for the median-priced, existing single-family home based on an 80% LTV ratio and a 25% DTI ratio (i.e., the mortgage payment amounts to 25% of total household income). The index applies the effective interest rate (as opposed to the contract rate). Multiplying the mortgage payment by 12 and dividing by the DTI yields the income necessary to qualify for a mortgage loan on the median-priced, existing single-family home. The index depicts the qualifying income divided by the area MFI; a value that equals or exceeds 100 indicates a household earning the area MFI can qualify for a mortgage loan on the median-priced, existing single-family home. A value below 100 indicates that a household earning the area MFI cannot qualify for a mortgage loan on the median-priced, existing single-family home. For example, an index value of 120 indicates that the median family income for that geography exceeds the income necessary to qualify for a mortgage for the median-priced home by 20% (Bourassa & Haurin, 2017; *Housing Affordability Index*, n.d.; O'Dell et al., 2004).

NAR also calculates a first-time homebuyer's affordability index. The methodology is quite similar to the HAI, but assumes a median home price for first-time buyers of 70%, an area MFI of 65%, and an LTV of 90%. Since the LTV is higher than 80%, the index incorporates private mortgage insurance of 0.5%, which is added to the effective interest rate. The HAI will always depict higher affordability than the first-time homebuyer's index due to the difference in the percentages applied to the median home price and median family income to determine affordability for first-time homebuyers (*Housing Affordability Index*, n.d.).

National Association of Home Builders - Housing Opportunity Index

The Housing Opportunity Index (HOI), produced by the National Association of Home Builders (NAHB), closely resembles the HAI in that the primary components of each are housing costs and income. (Both NAR and NAHB are trade associations whose purpose is to protect the interests of the real estate industry—i.e., realtors and builders.) The HOI is a retrospective measure in that it estimates "the share of homes sold in that area that would have been affordable to a family earning the local median income, based on standard mortgage underwriting criteria" (*Housing Opportunity Index (HOI) - NAHB*, n.d.).

The HOI reflects median family income figures for metropolitan areas computed by the Department of Housing and Urban Development (HUD). The HOI assumes principal and interest for a 30-year fixed rate mortgage. The DTI ratio measures 28%; the LTV, 90%, and the interest rate represents the average of the 30-year fixed effective rate from Freddie Mac's Primary Mortgage Market Survey. NAHB obtains sales transaction records from CoreLogic. Unlike the HAI, the HOI includes property taxes and insurance in the mortgage payment, which reflect metropolitan-wide estimates of property tax and insurance rates from the most current American Community Survey. In this sense, the HOI captures more of the housing costs incurred by the homeowner (*Housing Opportunity Index (HOI) - NAHB*, n.d.; Jewkes & Delgadillo, 2010; O'Dell et al., 2004).

Methodological Limitations of Indicators of Owner-Occupied Housing Affordability

Although widely promulgated, indicators of owner-occupied housing affordability present numerous limitations—encompassing a vast array of concerns—which diminish the ability of the indicators to accurately portray affordability. With respect to methodological limitations, the overarching criticism of indicators of owner-occupied housing affordability rests on their seemingly arbitrary, or ad hoc, nature: “All measures are based on judgments about which components of housing costs should be included and judgments about when these costs should be considered excessive” (Haurin, 2016, p. 1).

The four indicators of owner-occupied housing affordability present three primary methodological limitations (Hancock, 1993; Linneman & Megbolugbe, 1992; Thalmann, 2003):

1) the ad hoc nature of the indicators leads them to impose arbitrary thresholds which facilitate a dichotomous interpretation of affordability (i.e., a home becomes “unaffordable” past an arbitrary threshold),
2) a sole focus on median home price and household income, therefore failing to reflect affordability across the income and price distributions, and
3) a failure to consider the additional costs of homeownership.

Arbitrary Thresholds

Despite the significant advantages offered by indicators which adopt the ratio approach, these indicators present several limitations which may actually diminish or even negate their utility to users. Firstly, a long litany of criticism—voiced by both scholars and practitioners—surrounds the arbitrary nature of the thresholds imposed by both the HUD measure (i.e., establishing 30% and 50% as the cutoffs for cost-burdened and severely-cost burdened households, respectively) and the Median Multiple (i.e., determining that any geography with a value above 3.0 is “unaffordable,” albeit to varying degrees) (Cox & Pavletich, n.d.; Galster & Lee, 2020; Lerman & Reeder, 1987). In other words, measures which adopt the ratio approach encourage normative standards regarding the “appropriate” amount of household income that should be devoted to housing costs. These standards lack methodological rigor and lend themselves to a measure that is ambiguous in its interpretation. While there may be very little difference in the financial situations of two households which spend relatively similar proportions of income on housing costs (say, 29% and 30%), the HUD guideline automatically categorizes the latter household as cost-burdened. In short, the affordability designations are arbitrary and tell users little about the true nature of affordability (Hancock, 1993; Hulchanski, 1995; Thalmann, 1999, 2003).

The arbitrary nature of the indicators which reflect the ratio approach displays itself quite prominently through the distribution of income and home prices and the shape of each. For example, in the instance of the HUD measure, the lowest income households may not be able to reasonably afford housing costs which amount to 30% of household income, while the highest income households likely can reasonably afford to spend more than 30% of household income on housing costs (Bogdon & Can, 1997; Lerman & Reeder, 1987). Furthermore, with respect to homeownership, lower-income households may require higher qualifying (DTI) ratios to afford a home. Ceteris paribus, the lower the qualifying ratio, the lower the home price affordable to a particular household (Acolin, Bricker, et al., 2016; Pennington-Cross & Nichols, 2000).

Use of Median Home Prices and Household Income

The four most popular indicators of owner-occupied housing affordability measure the home purchasing potential of households earning either the median household or family income. Furthermore, the indicators estimate affordability for the median home price (Cox & Pavletich, n.d.; Jewkes & Delgadillo, 2010; O'Dell et al., 2004). In other words, relying on the median home price and household or family income, as opposed to the distribution of home prices and household or family income, diminishes the ability of the indicators to reflect affordability for the entire population (Gan & Hill, 2009). At present, the indicators of owner-occupied housing affordability are not representative of the entire population. The adoption of median home price and median household or family income proves particularly problematic in attempting to model affordability for lower-income households (i.e., those for whom affordability is more likely to be an issue). For households at the upper end of the income spectrum, tastes and preferences more significantly affect housing choice (i.e., the level of "affordability" acceptable to them) (Lerman & Reeder, 1987; Thalmann, 1999, 2003). However, at the lower end of the income spectrum, the budget constraints of households are such that few housing options are available to them.

Failure to Incorporate Additional Expenses

Aside from the arbitrariness of the HUD measure, with respect to owner-occupied housing, additional limitations include its failure to incorporate additional expenses—maintenance, origination points and fees, and closing costs—as well as benefits, such as property tax and mortgage interest deductions. The HUD measure also discounts the quality of both the housing and its surrounding environs (i.e., the neighborhood), although housing quality generally poses of less considerable concern due to the imposition of stricter construction standards over the past several decades (Bogdon & Can, 1997; Fisher et al., 2009; Lerman & Reeder, 1987). Furthermore, the HUD measure does not adjust for household size, which may significantly affect affordability—for example, it is possible for housing to be affordable to a particular household, but for that household to be underhoused (i.e., eight individuals living in a two-bedroom house) (Kutty, 2005). Moreover, the HAI does not consider the tax benefits of homeownership, home depreciation, home price appreciation, or the transaction costs incurred by either buyers or sellers (Bourassa & Haurin, 2017).

Issues in Assessing Reliability and Validity

Assessing the reliability and validity of indicators of owner-occupied housing affordability proves particularly challenging—each indicator offers vastly different interpretations. As home prices and household incomes may assume any positive value, the values of the Median Multiple may range from 0.01 to infinity, but are generally constrained to four categories: 1) below 3.0 (affordable), 2) 3.1 – 4.0 (moderately unaffordable), 3) 4.1 – 5.0 (seriously unaffordable), and 4) greater than 5.0 (severely unaffordable) (Cox & Pavletich, n.d.). Meanwhile, the values of the HAI may also range from 0.01 to infinity, but are generally constrained to three categories: 1) less than 1.0, which indicates that a family earning the median income would be unable to qualify for a mortgage loan for the median-priced home, 2) 1.0, which indicates that the median family income is exactly sufficient to qualify for a mortgage loan for the median-priced home, and 3) greater than 1.0, which suggests that a family earning the median income earns more than is necessary to qualify for a mortgage loan for the median-priced home (*Housing Affordability Index*, n.d.). Clearly, the Median Multiple and the HAI bear similar interpretations in the sense that both pose arbitrary thresholds below or beyond which homeownership is considered "unaffordable"; however, the values (or rather, the categories adopted by the indicators) vary significantly such that attempting to compare the results of the two proves dubious.

Toward an Improved Indicator of Purchase Affordability

In light of the comprehensive review of the limitations of existing indicators of purchase affordability, this research proposes several suggestions for scholars, practitioners, and policymakers to consider in the development of a new indicator of purchase affordability.

- Existing indicators encapsulate purchase affordability for broad geographic scales—states, MSAs, counties, etc. However, the affordability problem exists at the individual household level. Moreover, existing indicators reflect median home prices and median household (or family) income, which diminishes the potential for users to estimate affordability across the income or price distributions. Planning practitioners and housing policymakers would be able to more effectively target policy implementations with greater knowledge of the affordability problems facing individual households.
- The overwhelming majority of households in the U.S. depend on mortgage financing to purchase a home—86% in 2020 (Oppler, 2020). Only a few indicators of purchase affordability incorporate select components of mortgage financing, but none of the indicators allows these components to fluctuate based on the characteristics of the

borrower. For instance, the HAI and HOI apply universal DTI ratios (25% and 28%, respectively) and LTV ratios (80% and 90%, respectively) (*Housing Affordability Index*, n.d.; *Housing Opportunity Index (HOI) - NAHB*, n.d.). It is well-established that the borrowing constraints vary considerably among individual households based on the type of loan originated (i.e., conventional, FHA, VA, or RHS); as such, it makes little sense to promulgate indicators that apply singular values to the borrowing constraints (and do not let users adjust these constraints) (Baeck & DeVaney, 2003; Foote, 2010b, 2010a; Jones, 2018; McCarty et al., 2019). Meanwhile, the existing indicators of purchase affordability largely apply to borrowers with conventional mortgage financing. There are presently no indicators of purchase affordability for borrowers with federally-backed mortgages. Indicators should quantify purchase affordability separately for each loan type to allow for the application of more representative borrowing constraints.

- As mentioned in the previous point, existing indicators generally focus singularly on home purchasing potential for median income earners (i.e., the indicators reflect the ability of a household earning the median income to afford the median-priced home) (Gan & Hill, 2009). However, it is apparent that purchase affordability proves a problem predominantly for the lowest-income households. Existing indicators of housing affordability largely fail to distinguish the neediest households from those for whom housing affordability largely proves a function of tastes and preferences (Thalmann, 1999, 2003).
- Measure both supply and demand. The definitions of housing affordability generally position it as a function of both household demand (i.e., income) and housing supply (i.e.,

housing costs). However, generally speaking, existing indicators solely reflect household demand, which paints only half the picture of affordability (Bourassa & Haurin, 2017; Haurin, 2016). By failing to provide a measure of housing supply, these indicators are able to say little about affordability.

Origins of Neighborhood Opportunity

For nearly a century (since the inception of the Chicago School in the 1920s), scores of scholars across a variety of disciplines have studied the relationship between households and neighborhoods, dedicating particular attention to the ways in which individuals interact with the built environment and the effects of the neighborhood on its inhabitants (Lung-Amam et al., 2018; Lutters & Ackerman, 1996). A long litany of literature in sociology, economics, and, most recently, urban planning, attempts to discern these effects. The “geography of opportunity” does not represent a new concept, but rather succeeds concepts, including “concentrated poverty,” “neighborhood disadvantage,” and “neighborhood effects,” perhaps the most all-encompassing of the terms, which have long swirled in the social sciences (Lens, 2017; Sampson et al., 2002; South & Crowder, 1999). Galster and Killen significantly reshaped the discourse that previously dominated the field by reframing the negative connotations borne by such terms—i.e., “poverty” and “disadvantage”—as neighborhood “opportunity” (Galster & Killen, 1995).

Coined in 1995 in a seminal article by George Galster and Sean Killen, the “geography of opportunity,” which denotes the “spatial pattern of factors that shape the structure of opportunity in metropolitan regions,” (Knaap, 2017, p. 913) was born amidst the implementation of several governmental housing mobility programs—perhaps the most notable of which include Moving to

Opportunity and Gautreaux (Duncan & Zuberi, 2006; Galster & Killen, 1995). Moving to Opportunity, which followed a quasi-experimental design, randomly assigned families living in public housing in Baltimore, Boston, New York City, Chicago, and Los Angeles to receive either no additional housing assistance or one of two housing vouchers: a treatment group received vouchers to relocate to neighborhoods with less than a 10% poverty rate, while the experimental group received vouchers to relocate to a neighborhood of their choosing (Duncan & Zuberi, 2006; Katz et al., 2001; Kling, 2008). In the Gautreaux program, families living in public housing in Chicago received vouchers to move to neighborhoods with an African American population which comprised less than 30% of the total population; 75% of voucher recipients were to move to the suburbs. Vouchers were not randomly assigned, introducing selection bias (Rosenbaum, 1995; Rosenbaum & Zuberi, 2010).

Conceptual Limitations of the Geography of Opportunity

As outlaid by Galster and Killen, the geography of opportunity consists of two key elements: the opportunity structure and the opportunity set. The opportunity structure, or the "process" aspect of opportunity, "refers to the way markets, institutions, and service delivery systems (e.g., the social welfare or educational system, legal and illegal labor markets, the criminal justice system, or the housing market) utilize and modify the innate and acquired characteristics of participants" (G. C. Galster & Killen, 1995, p. 9). The "prospect" aspect of opportunity, or the opportunity set, "refers to the prospective socioeconomic outcomes (likely streams of future income, consumption, and utility) that people believe will occur if they make particular decisions regarding education or work" (9). The normative aim of equality undergirds the geography of opportunity—within this particular framework, it translates as such: households should have equal access to equal opportunities (Dawkins, 2017; Imbroscio, 2016b). Embedded in the distributional ideal of equality is the uniformity of opportunity structures: any differences which manifest themselves in individuals' life outcomes will be due to autonomous choices, disparities in innate abilities (primarily intelligence), or disparities in familial circumstances (or some combination thereof) (Ellen & Turner, 1997).

Meritocracy proves a particularly pernicious element of the geography of opportunity (Imbroscio, 2016b; Knaap et al., 2014). The underlying premise follows as such: in the current environment, individuals are unfairly and unduly constrained in access to opportunities. (In other words, opportunity structures differ significantly among individuals as a result of deleterious market forces and practices.) Removing these constraints by facilitating equality—equal access to equal opportunities—will allow individuals to reach their full potential, reducing disparities in individuals' life outcomes to individual merit (i.e., intelligence, skills, ability, etc.) (Popkin, 2016; Silverman, 2016). However, this vastly ignores the indelible role played by other individuals—particularly family and perhaps friends—that shape individuals' life outcomes (Ellen & Turner, 1997; Imbroscio, 2016a). Diminishing disparities in access to opportunities will likely yield positive results up to a certain threshold, beyond which individuals' life outcomes become a factor *both* of familial upbringing, social support networks, discrimination, etc. *and* merit. Leveling opportunity between neighborhoods does not necessarily equalize individuals' ability to reach their full potential based on their merit—other external factors, such as racial discrimination, may inhibit such an aim (Baker, 2015; Galster, 2019; G. Galster & Santiago, 2017).

History in Federal Housing Policy

Although a primary facet of federal housing policy for over fifty years (since the Civil Rights Movement), fair housing recently received renewed attention. While perhaps most well-known for prohibiting discrimination in the sale or rental of housing on the basis of race, color, religion, sex, national origin, age, disability, and familial status, the Fair Housing Act of 1968 also bore a second, albeit lesser-known goal: reducing racial segregation by facilitating diverse, inclusive communities, broadly known as Affirmatively Furthering Fair Housing (AFFH) (Menendian, 2017; K. M. O'Regan, 2019; O'Regan & Zimmerman, 2019).

The Act deemed HUD the federal authority responsible for overseeing programs that concerned fair housing: "HUD was authorized to affirmatively further fair housing (AFFH) in all of its programs and funded activities" (Silverman et al., 2017, p. 143). However, the parameters of this mandate proved dubious, leading to its haphazard enforcement across local jurisdictions. In the decades following the passage of the Fair Housing Act, jurisdictions (state and local governments) which received HUD funding for housing and community development initiatives implemented few measures to satisfy the provision of AFFH. In 2015, under the Obama administration, HUD implemented a new rule that increased oversight of those jurisdictions by requiring them to identify and redress any fair housing issues, including housing practices and barriers to fair housing (Haberle et al., 2020; Hensley, 2019; Jargowsky et al., 2019). Overarchingly, the new interpretation of the AFFH provision encompassed the broader mission of the Obama administration to facilitate neighborhood opportunity. Jurisdictions document these fair housing issues in the mandatory Assessment of Fair Housing (AFH) (Menendian, 2017).

To assist jurisdictions in writing the AFH, HUD developed a comprehensive dataset and mapping platform, known as the AFFH Data and Mapping Tool (AFFH-T), which publishes information on sociodemographic and neighborhood characteristics. The AFFH-T evaluates disparities in access to opportunity through a two-stage process: 1) quantifying the degree to which a neighborhood offers features commonly viewed as important opportunity indicators, including education, employment, and transportation and 2) comparing these rankings across people in particular racial and economic subgroups to characterize disparities in access to opportunity (Mast, 2015; Silverman et al., 2017). Since 2015, HUD has published six iterations of the AFFH-T, the most recent of which was published in July 2020 (Gourevitch, 2018). Although HUD Secretary Ben Carson repealed the AFFH rule in the midst of the Trump administration, the Biden administration appears poised to reinstate the rule (Dane, 2019).

People- vs. Place-Based Housing Policy

At the intersection of fair housing and community development, a decades-long debate lingers over the appropriate means by which to facilitate households' access to high-opportunity neighborhoods. The two seemingly contending spheres—people- and place-based housing policy—both aim to improve the socioeconomic outcomes of lower-income households, but display significant differences as to the appropriate means by which to accomplish such an objective. People-based housing policy encourages low-income households to relocate to higher-opportunity neighborhoods, whereas place-based housing policy seeks to revitalize the neighborhoods in which low-income households reside to improve opportunity. While the two policies are clearly at odds—the first seeks to relocate low-income households and the second facilitates the ability of such households to remain in place, both seek to facilitate the access of low-income households to high-opportunity neighborhoods (Galster, 2017; Galster, 2019; O'Regan, 2017; Owens, 2017).

The community development field favors place-based housing policy, arguing that directing investment to existing neighborhoods allows residents to remain in place and maintain community ties. However, proponents of people-based housing policy (generally those in the housing and planning fields) contend that place-based housing policy does not redress the market practices and institutional forces, such as racial discrimination, that have beleaguered these communities for decades. Instead, those who support people-based housing policy posit that it diminishes racial and economic inequality by promulgating mixed-race, mixed-income neighborhoods. A significant flaw of people-based housing policy is that it disadvantages low-income homeowners, as the majority of programs and policies that support the first approach offer federal housing assistance to low-income renters (Dawkins, 2017; Green, 2015; Lung-Amam et al., 2018; Shelby, 2017). Of course, neither people- nor place-based housing policy offers a perfect solution to facilitate the access of low-income households to high-opportunity neighborhoods. Both approaches present several limitations which must be sufficiently addressed for the approach to provide the most desirable outcomes for households (Owens, 2017).

Relocation may fail to yield significant improvements in the socioeconomic outcomes of those households. In other words, lower-income households living in high-opportunity neighborhoods may not necessarily reap the same benefits as higher-income households—for example, lower-income households may not witness greater employment opportunities without supplemental training programs or other mechanisms designed to bolster employment potential (Davidson, 2009; Dillman et al., 2017; Shelby, 2017). Furthermore, relocating low-income households to higher-opportunity neighborhoods may fragment the existing social and community ties of those households. Perhaps the most damning and pernicious criticism of people-based housing policy, however, stipulates that facilitating relocation may increase spatial inequality and perpetuate pockets of disadvantage by failing to improve existing low-opportunity neighborhoods. In other words, relocating low-income households to high-opportunity neighborhoods fails to address the underlying forces that promulgate socioeconomic disparities, such as racial discrimination (Goetz, 2015; Owens, 2017).

Meanwhile, despite investing in low-opportunity neighborhoods, placed-based housing policy may not necessarily alter the existing (potentially counterproductive) social environment that may permeate such neighborhoods. Furthermore, place-based housing must work within the confines of the potentially noxious physical landscape of low-opportunity neighborhoods, in which landfills and heavy industry are likely to be disproportionately sited (and unlikely to be removed) (Kershaw et al., 2013; Yandle & Burton, 1996). Place-based housing policy may perpetuate racial and economic disparities by continuing to relegate low-income and minority households to “pockets of disadvantage.” Meanwhile, without the implementation of specific programs to address such matters, place-based housing does not increase the employment or economic opportunities available to households (Lung-Amam et al., 2018; O’Regan, 2017).

Limitations of People- and Place-Based Housing Policy

Both people- and place-based housing policies pose enormous conceptual limitations, which ultimately diminish their ability to redress the inequitable socioeconomic outcomes faced by households in marginalized and disadvantaged communities (Galster, 2017b; Goetz, 2015; Turner, 2017). The policies involve the interference of the government with respect to households' residential location (in the instance of people-based housing policy) or neighborhood conditions (in the case of place-based housing policy) (Jennings, 2012). The policies, which attempt to facilitate access to higher quality amenities and resources and better socioeconomic outcomes for households in low-opportunity neighborhoods and are imbued with rationalism, make several assumptions:

1) Low-income populations (who are disproportionately sited in low-opportunity neighborhoods) should aspire to live in neighborhoods with conditions similar to those of opportunity-rich neighborhoods, which are largely inhabited by white, middle- and upper-class individuals (Dawkins, 2017).

People- and place-based housing policies depend heavily on the scientific models generated by quantitative measures of neighborhood opportunity—specifically, opportunity indexes and opportunity mapping (Finio et al., 2020). Neighborhood opportunity emerges as a relative concept—i.e., neighborhood opportunity is deemed "low" or "high" by comparing the scores of one neighborhood to the scores of all neighborhoods within a particular geography (typically a city or county) (Knaap, 2017). This comparative framework perpetuates the notion that opportunity-rich neighborhoods should set the precedent for the "ideal" neighborhood (Wilson & Greenlee, 2016).

2) The neighborhood in which the household lives has deteriorated to such a state that it should be altered through community reinvestment and revitalization or abandoned in favor of relocation to opportunity-rich neighborhoods (Green, 2015; Wang et al., 2017).

Again, the comparative nature of measures of opportunity mapping instills the notion that neighborhoods can be characterized as “good” or “bad”—i.e., of “high,” “medium,” or “low” opportunity (Knaap, 2017; Lung-Amam et al., 2018; Lung-Amam & Dawkins, 2020). This implies that the neighborhoods with the lowest opportunity scores are problematic, even though 1) the inhabitants of such neighborhoods may actually disagree with such a sentiment and 2) this promulgates the notion that neighborhoods with comparatively low opportunity scores are a “drain” on society (Galster & Sharkey, 2017). Scoring opportunity (i.e., encouraging measures which numerically quantify opportunity) may perpetuate discriminatory notions held by particular households—particularly white households (who are disparately represented in higher-opportunity neighborhoods) toward the residents of “low-opportunity” neighborhoods (Goetz, 2017).

3) Households in lower-opportunity neighborhoods should aspire to the same socioeconomic outcomes of households in opportunity-rich neighborhoods.

It is assumed that the beneficiaries of people- or place-based housing policies 1) will utilize their newfound access to higher quality resources and amenities (such as better schools, jobs, etc.) and 2) aspire to the same socioeconomic outcomes as the upper echelon of society. Of course, the fallacy of this notion rests in the simple fact that individual preferences differ: individuals aspire to different levels of educational attainment, kinds of jobs, etc. (Ellen &

Turner, 1997; Galster, 2018; Popkin, 2016). To be quite clear, the differences which exist in individual preferences dictates nothing about individual ability, but merely recognize that, faced with the exact same resources and amenities, the socioeconomic outcomes of two individuals may not be the same due to the way each individual chooses to utilize the resources and amenities available to him or her, as well as external forces, such as racial discrimination and segregation, which inhibit neighborhood choice (Bergman et al., 2019).

4) The spatial disparities in neighborhood opportunity and socioeconomic outcomes of households necessitates government interference. Inherent to people- and place-based housing policies is the notion that, as spatial disparities in neighborhood opportunity can be objectively proven, the inefficient and inequitable nature of such disparities warrants government interference to redistribute either people or resources (Patterson et al., 2015; Silverman et al., 2017).
5) Perhaps the most pernicious—individuals living in marginalized and disadvantaged communities are helpless, powerless, and/or lack the necessary knowledge to warrant their involvement in the policy-making process (Green, 2015; Lung-Amam et al., 2018; Shelby, 2017). People- and place-based housing policies promulgate the notion that external forces with expert knowledge are the optimal decision makers in the process of the redistribution of households or resources (Turner, 2017).
6) The policies largely rely on objective measures of neighborhood opportunity (particularly opportunity mapping and opportunity indexes) to develop indicators of neighborhood opportunity and establish a basis by which to characterize each neighborhood. These measures are fraught with their own conceptual limitations, one

of the most significant of which is the issue of the variables embedded in the measures. While these measures are produced from a consistent methodology, the set of variables that ought to be included in these measures remains a lingering issue (Goetz, 2017; Knaap, 2017). This diminishes the ability of people- and place-based policies to produce the intended results.

Opportunity Mapping

Pioneered approximately two decades ago, opportunity mapping, the chief method used to measure and visualize neighborhood opportunity, proves pervasive in planning and policy. Derived from a confluence of methods developed over several decades, including suitability analysis and equity mapping, HUD recently introduced its own series of Opportunity Indexes, which form the basis for such maps (Gourevitch, 2018; Knaap et al., 2014). The widespread growth in the popularity of opportunity mapping can be attributed to two concurrent phenomena: the rise of research on the geography of opportunity (and increased attention from policymakers) and the development of GIS, a tool used to create maps (Galster, 2017b).

Opportunity may be spatialized through a myriad of variables, such as poverty, jobs accessibility, school quality, and environmental health hazards. Neighborhoods are typically graded on a Likert scale (i.e., low- to high-opportunity), allowing users of opportunity maps to readily identify inequalities in the distribution of "opportunity" across a particular geography—i.e., pockets of low- and high-opportunity (Knaap, 2017). The Kirwan Institute, a leading producer of opportunity maps across the United States, defines the practice as a "research tool used to understand the dynamics of 'opportunity' within metropolitan areas…to illustrate where opportunity rich communities exist (and assess who has access to these communities) and to understand what needs to be remedied in opportunity poor communities" (*New Orleans Opportunity Mapping – An Analytical Tool to Aid Redevelopment | Kirwan Institute for the Study of Race and Ethnicity*, n.d.).

History

Opportunity mapping traces its roots to a fight over fair housing in the city of Baltimore: in 2003, John Powell, who pioneered opportunity mapping, utilized it in the case of Thompson vs. HUD (Tegeler et al., 2011). The plaintiff argued that the city of Baltimore had disproportionately sited minorities and public housing in disadvantaged neighborhoods. He presented a series of maps depicting an aggregate opportunity index that incorporated variables within three categories: economic opportunity and mobility, educational opportunity, and neighborhood health (DeLuca & Rosenblatt, 2017; Knaap et al., 2014). His application of opportunity mapping proved a powerful and persuasive testimony of the disparities in the resources and amenities faced by Baltimore's African American households. The case resulted in the implementation of a voucher program in which recipients moved to neighborhoods with a population of less than 30% African Americans, a poverty rate of less than 10%, and fewer than 5% of households with Housing Choice Vouchers (powell, 2003).

Operationalizing "Opportunity"

Opportunity mapping generally follows a fairly routinized methodology, originally outlaid by the field's pioneer, John Powell, in the first series of opportunity maps, and subsequently codified by the Kirwan Institute. In his *Thompson vs. HUD* testimony, Powell showcased a series of opportunity maps which depicted neighborhood opportunity along three spectrums: 1) economic opportunity and mobility, 2) educational opportunity, and 3) neighborhood health (powell, 2003). He selected underlying data to represent each category and compiled that data into individual opportunity indexes at the Census tract level. He then combined the three individual indexes into an aggregate index. After converting the raw data for the aggregate index into Z-scores, he mapped the aggregate index using a quintile distribution, which divided the 615 Census tracts in Baltimore into five categories (each with 123 Census tracts). Powell labeled the five categories “Very Low Opportunity,” “Low Opportunity,” “Moderate Opportunity,” “High Opportunity,” and “Very High Opportunity,” and color-coded the map accordingly (Knaap et al., 2014; Reece, 2019). The impact of Powell’s testimony cannot be overstated: the opportunity maps produced by the Kirwan Institute, which remains one of the key producers of opportunity maps across the United States, adopted his methodology (Tegeler et al., 2011).

The underlying data, or indicators, used to manifest Powell’s index of economic opportunity and mobility included: 1) proximity to recent job growth 1998-2002, 2) proximity to potential entry level and low-skill jobs 2002, 3) ratio of entry level and low skill employment opportunities per 1,000 residents, 4) proximity (within a ½ mile) of public transit lines, and 5) median commute to work time. The underlying data, or indicators, used to manifest Powell’s index of educational opportunity consisted of the 1) proportion of students eligible for free and reduced lunch, 2) proportion of classes not taught by highly qualified teachers, 3) proportion of elementary students proficient in reading, and 4) proportion of elementary students proficient in math. The underlying data, or indicators, used to manifest Powell’s index of neighborhood health included the 1) rate of population change from 1990 to 2000, 2) neighborhood poverty rates in 2000, 3) median owner-occupied home values in 2000, 4) property vacancy rates, and 5) estimated crime index in 2000 (Knaap, 2017; powell, 2003; Silverman et al., 2017).

Despite differences in the underlying data and/or the categories used to manifest opportunity, the entities which produce opportunity maps largely utilize the methodology developed by Powell and the Kirwan Institute (Keane, 2007; Tegeler et al., 2011). The development of such maps generally proceeds as follows: 1) identify the variables to be included in the opportunity index and designate specific categories (i.e., housing and neighborhood indicators, economic indicators, transportation and mobility indicators, etc.) that will be used to compute the composite opportunity index, 2) collect the data, 3) normalize the data and assign the data to the appropriate category, 4) calculate the aggregate opportunity index, 5) generate the map, and 6) overlay other independent variables on the map (Finio et al., 2020; Knaap, 2017; Knaap et al., 2014). However, despite the implementation of a standard statistical approach to facilitate opportunity mapping, the field faces several lingering conceptual issues, particularly with respect to the variables incorporated.

Limitations of Opportunity Mapping

The proliferation of opportunity mapping as a technique for both scholars and practitioners to guide planning and policy decisions related to the distribution of housing and other social services renders a comprehensive assessment of its limitations quite crucial. Although seemingly “logical and straightforward upon first inspection,” the methodology underlying the vast majority of opportunity maps invites a series of criticisms, particularly with respect to its validity, of which there as yet remains little knowledge: “there exists no published discussion among researchers or practitioners that examines the utility and soundness of the technique” (Knaap, 2017, p. 917). The apparent lack of methodological rigor identified in the practice proves particularly problematic in light of its ubiquity. Indeed, Knapp postulates that, in addition to a lack of understanding of definitions of opportunity mapping, significant pitfalls surround its operationalization:

1) It may not accurately measure the phenomena it attempts to capture (i.e., its construct validity must be questioned). The variables used to compute opportunity indices are often subjective—for instance, specifying a 10% poverty rate as the threshold at or beyond which a neighborhood shifts to “low-opportunity” proves dubious (Dawkins, 2017; Galster, 2018).
2) The role of neighborhood effects in shaping individual outcomes varies for households and even within households (i.e., among members within any given household); opportunity mapping assumes that neighborhood effects are equally distributed across households within a particular neighborhood (Ellen & Turner, 1997).
3) Moreover, the opportunity indexes which undergird opportunity maps do not capture nonlinearity. For example, the scores for the HUD Opportunity Indexes range from 0 to 100. The continuous range indicates that an increase in a particular index from 50 to 60 bears the same effect as an increase from 60 to 70. In reality, there may be critical values or a certain threshold beyond which “opportunity” significantly changes (Galster, 2018).
4) The geographic boundaries used to compute neighborhood opportunity are randomly configured. While users of opportunity mapping generally apply widely-accepted

geographical boundaries developed by the U.S. Census Bureau (primarily the Census tract or block group), it nonetheless must be recognized that such boundaries are subjective and may distort the results (Deng, 2016; Lens, 2017). For instance, a household situated on the boundary between two neighborhoods, one with a higher poverty rate and the other with a low poverty rate, may not share the same experiences as a household located in the middle of either neighborhood. Opportunity mapping doesn't adjust for the location of individual housing units, but rather depends on results at an aggregate level (Coulton et al., 2013).

5) It generally fails to capture the social dimensions embedded within neighborhoods (i.e., social support networks), which can be particularly critical for low-income households. While it proves considerably more difficult to quantify, for instance, social capital, it may bear significant clout for households (Green, 2015).

6) It usually fails to consider the variables which bear the most significance for households within a particular neighborhood—scholars or practitioners may place greater weight, for instance, on the poverty rate in constructing the opportunity index than, say, access to employment. In actuality, the residents of a particular neighborhood may value access to employment more highly. While input from community members does not signify a necessary component of opportunity mapping, without public participation, the results may not accurately portray the underlying phenomena most crucial to residents (Finio et al., 2020; Lung-Amam et al., 2018; Lung-Amam & Dawkins, 2020).

7) It imposes normative standards on the neighborhoods which households ought to occupy—i.e., it ranks neighborhoods on a scale from low- to high-opportunity. This may

encourage users to perceive of low-opportunity neighborhoods, generally home to lower-income households, as "undesirable" (Dawkins, 2017; Lung-Amam et al., 2018)

CHAPTER IV

METHODOLOGY

The literature presently poses several gaps in the fields of owner-occupied housing affordability and neighborhood opportunity, both as individual and interconnected subjects. Existing literature on owner-occupied housing affordability suffers from methodological challenges with respect to 1) modeling purchase affordability and 2) modeling purchase affordability for federally-backed mortgages (Baeck & DeVaney, 2003; Dokko, 2018; Haurin, 2016; Jewkes & Delgadillo, 2010; O'Dell et al., 2004). Meanwhile, although scholars continue to bridge the gap between the fields of renter-occupied housing affordability and neighborhood opportunity, the fields of owner-occupied housing affordability and neighborhood opportunity remain relatively distinct (Acevedo-Garcia et al., 2016; Walter & Wang, 2016). As yet, a paucity of studies examines the relationship between the two fields (Heidelberg & Eckerd, 2011). Moreover, no study yet addresses the limitations presented by existing indicators of purchase affordability.

This research seeks to bridge the gap between a specific type of owner-occupied housing affordability—purchase affordability—and neighborhood opportunity. Existing indicators of purchase affordability reflect a broad array of limitations (Bourassa & Haurin, 2017; O'Dell et al., 2004; Quigley & Raphael, 2004):

1) The indicators typically do not reflect the various components of mortgage financing (such as the interest rate, loan term, etc.), instead focusing solely on home price and household income (and generally median home price and household income). The

indicators which do include the components of mortgage financing impose pre-determined (i.e., nonmodifiable), single values for the mortgage interest rate, loan term, etc.

2) The indicators fail to consider differences in purchase affordability among the types of loans—specifically, variations in purchase affordability among federally-backed mortgages. Mortgage financing terms tend to deviate substantially between conventional and federally-backed mortgages (Baeck & DeVaney, 2003; Foote, 2010b; Jones, 2018; Pennington-Cross & Nichols, 2000; Scally & Lipsetz, 2017).
3) The indicators do not compute purchase affordability across the home price and income distributions.
4) The indicators broadly fail to reflect the locational attributes embedded in housing, but instead model purchase affordability as an independent entity—that is, as distinct from neighborhood opportunity (Fisher et al., 2009). These research gaps prove particularly acute in the context of loan type—whether in the comparison between conventional and federally-backed mortgages or among federally-backed mortgages.

This research overcomes many of the current shortcomings by considering 1) the differences in purchase affordability among the loan types and across the home price and income distributions and 2) the relationship between purchase affordability and neighborhood opportunity.

Research Design

This research design uses cross-sectional data to 1) develop an improved indicator of purchase affordability, 2) assess the relationship between purchase affordability and neighborhood opportunity, including the potential effects of federally-backed mortgages, and 3) build a new framework by which to model purchase affordability and neighborhood opportunity conjointly. The research design positions these objectives within the context of 1) geographies of varying population size and housing challenges and 2) conventional, FHA-insured, VA-guaranteed, and RHS-guaranteed mortgage loans. This research relies solely on secondary data collected from a variety of sources, including the U.S. Census Bureau, HUD, and CFPB/HMDA.

Research Questions

This research aims to 1) develop an improved indicator of purchase affordability, 2) model purchase affordability and neighborhood opportunity, and 3) introduce a new framework which relates purchase affordability and neighborhood opportunity. Specifically, it addresses the following questions:

1) How does purchase affordability differ among the four loan types?
2) How do purchase affordability and neighborhood opportunity affect each other? What effect, if any, do federally-backed mortgages bear on the relationship?
3) How can planners, policymakers, and practitioners conjointly measure purchase affordability and neighborhood opportunity?

Study Sites

This research examines purchase affordability and neighborhood opportunity within three geographies in Texas: the Austin-Round Rock MSA (which encompasses five counties—Bastrop, Caldwell, Hays, Travis, and Williamson), McLennan County (home to Waco), and

Anderson County (home to Palestine). As one of the primary purveyors of federally-backed mortgages, Texas is an ideal state in which to study purchase affordability for borrowers of such mortgages. In 2019, Texas ranked third (behind California and Florida) with respect to originations of both FHA-insured and VA-guaranteed mortgages, which comprised 8.87% and 8%, respectively, of such mortgages nationwide. Meanwhile, among the 99,322 Section 502 RHS mortgages guaranteed nationwide, Texas represented nearly 3%, for a total of 2,673 loans. These trends did not deviate significantly from 2018 (*HMDA Data Publication*, n.d.).

Moreover, the three geographies present different scenarios with respect to purchase affordability and neighborhood opportunity. The Austin-Round Rock MSA, the fourth largest MSA in Texas, faces severe affordability constraints, precipitated both by rapid population growth and supply shortages. McLennan County, with a population of approximately 250,000, represents a relatively affordable mid-sized area. Meanwhile, Anderson County, a small, rural county with a population of approximately 60,000, proves the most affordable of the three. Meanwhile, the Austin-Round Rock MSA depicts stark disparities in neighborhood opportunity, whereas it experiences little differentiation in Anderson County. Table 4.1 provides an overview of the demographic and housing characteristics of the study sites in 2019.

Table 4.1 Demographic and Housing Characteristics of the Study Sites (2019)

	Anderson County	Austin-Round Rock MSA	McLennan County
Population	57,810	2,114,441	251,089
Occupied Housing Units	16,677	764,989	90,054
% Owner-Occupied	69.6%	58.2%	59.2%
Median Home Price	$130,000	$315,000	$190,500

Median Family Income	$53,519	$95,165	$62,727

Source: U.S. Census Bureau, 2019 American Community Survey, Texas Real Estate Research Center

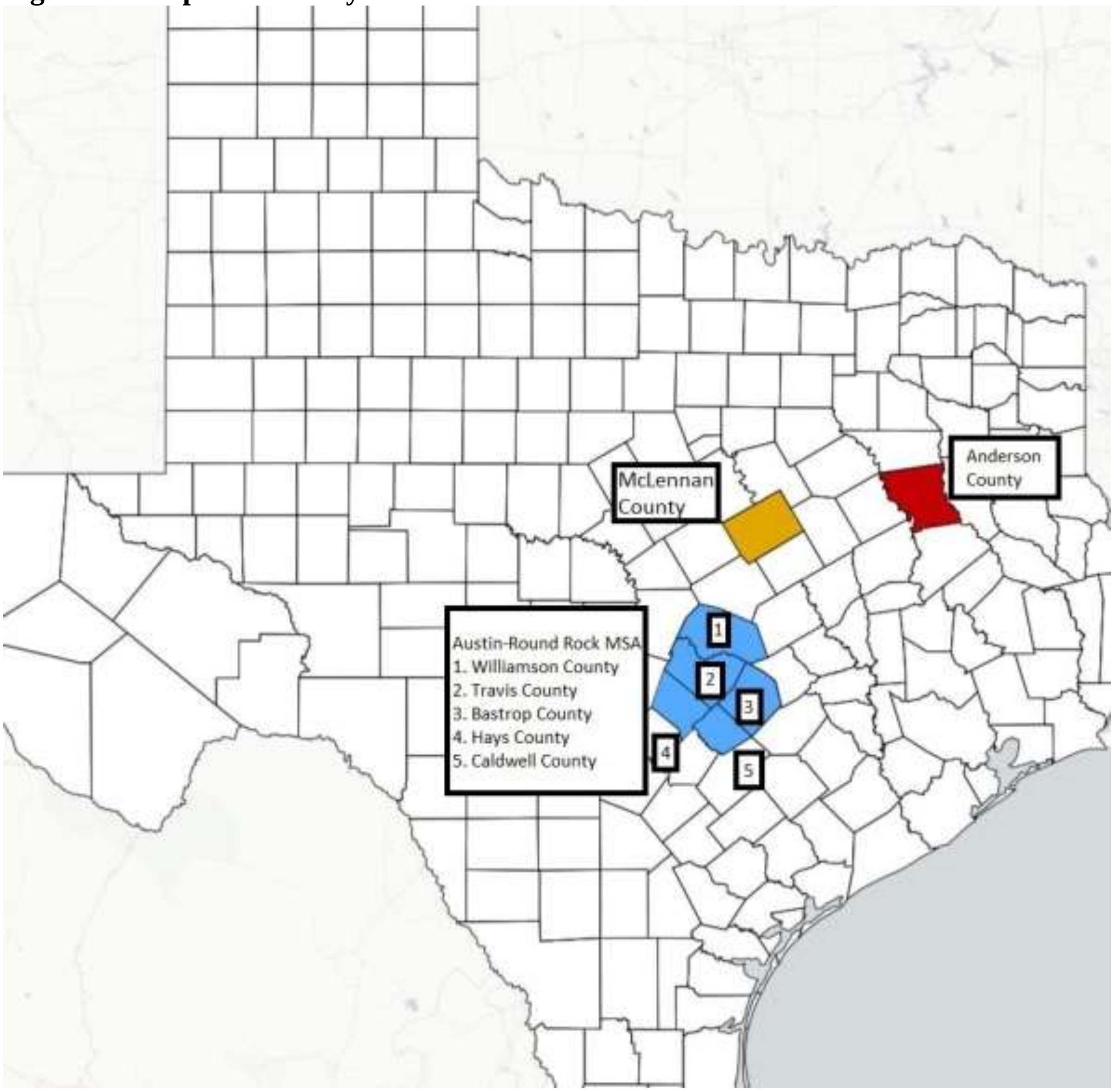
As depicted in Table 4.2, the anticipated population growth rates vary considerably among the study sites. For instance, the population of Anderson County is expected to remain fairly stagnant, with an anticipated growth rate of 4.5% over the ensuing five decades (from 2020 to 2070). Meanwhile, the population of McLennan County is expected to experience stronger growth—35.9%—over the same period. However, the Austin-Round Rock MSA is posed to experience precipitous population growth, ranging from a 72% increase in Travis County to a 302% increase in Bastrop County. This will particularly strain purchase affordability in the Austin-Round Rock MSA.

Table 4.2 Population Projections for the Study Sites, 2020-2070

County	**2020**	**2030**	**2040**	**2050**	**2060**	**2070**	**Change in Population, 2020-2070**
Anderson	61,016	63,017	63,746	63,746	63,746	63,746	4.5%
McLennan	252,211	272,216	289,887	307,661	325,373	342,757	35.9%
Bastrop	95,487	125,559	164,648	217,608	289,140	384,244	302.4%
Caldwell	47,008	57,553	67,955	78,243	88,639	98,754	110.1%
Hays	238,862	313,792	398,384	474,801	593,384	728,344	204.9%
Travis	1,298,624	1,538,784	1,767,636	1,936,583	2,075,875	2,233,259	72.0%
Williamson	631,097	771,834	941,827	1,141,301	1,394,412	1,643,646	160.4%

Source: Texas Water Development Board

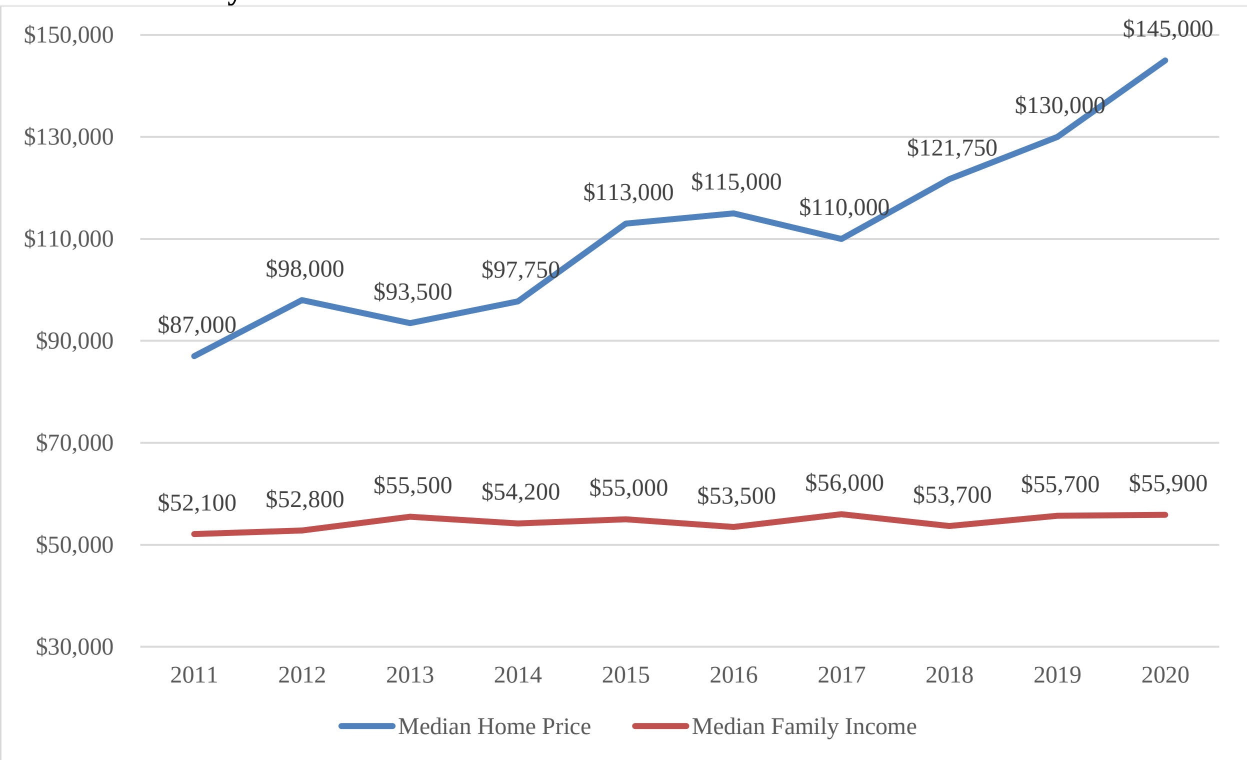
Figure 4.1 Map of the Study Sites



Purchase Affordability in the Study Sites

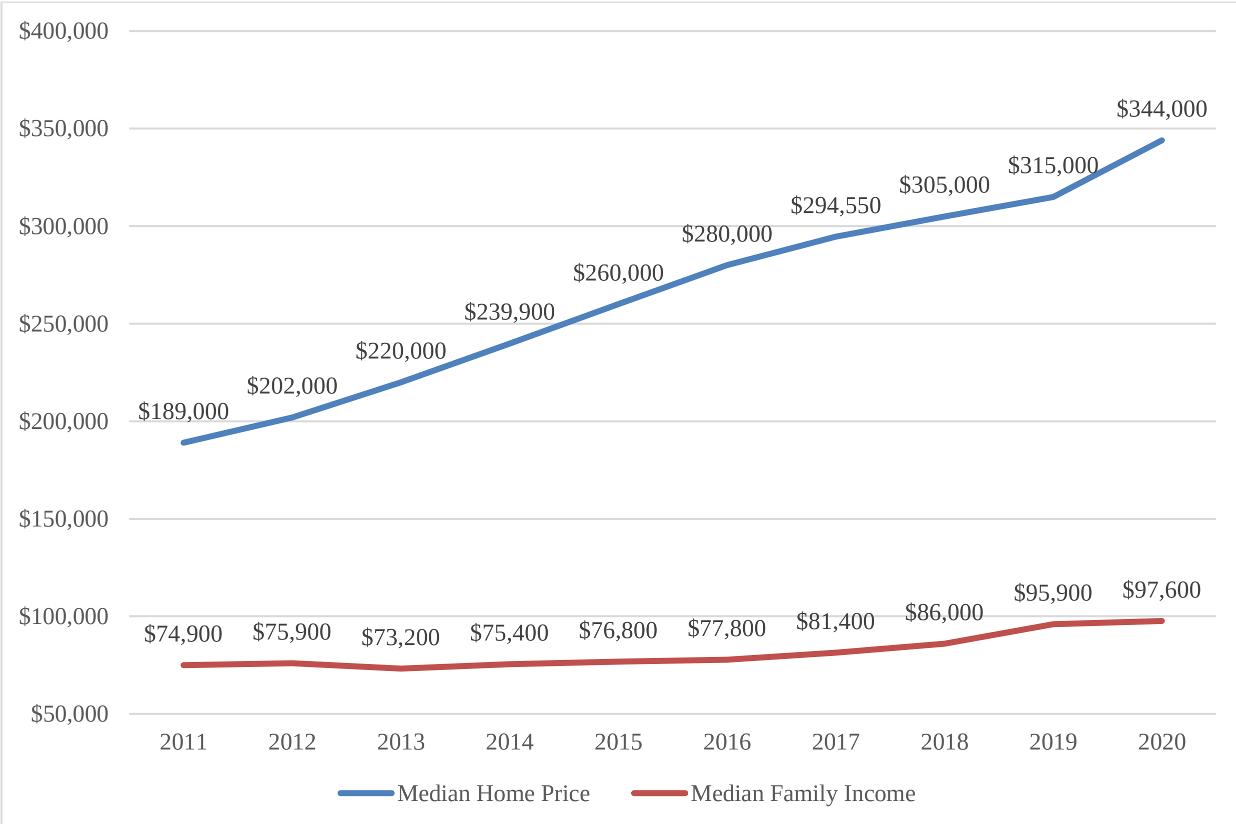
Although the study sites face vastly different challenges with respect to homeownership and neighborhood opportunity, purchase affordability proves a growing concern among all three. Since the end of the Great Recession, the widening divergence between median home price and median family income has eroded home purchasing potential, particularly for lower-income households (Gaines & Losey, n.d.). In Anderson County, the median home price measured 2.6 times median family income in 2020, compared to a mere 1.7 times median family income in 2011. Meanwhile, from 2011 to 2019, the median home price in the Austin-Round Rock MSA nearly doubled (82%), whereas median family income only increased by nearly one-third (30%). A similar phenomenon occurred in McLennan County, in which median home price increased by 76% and median family income by 22%. Figures 4.1-4.3 depict the growth in median home price and median family income in each study site.

Figure 4.2 Comparison between Median Home Price and Median Family Income in Anderson County



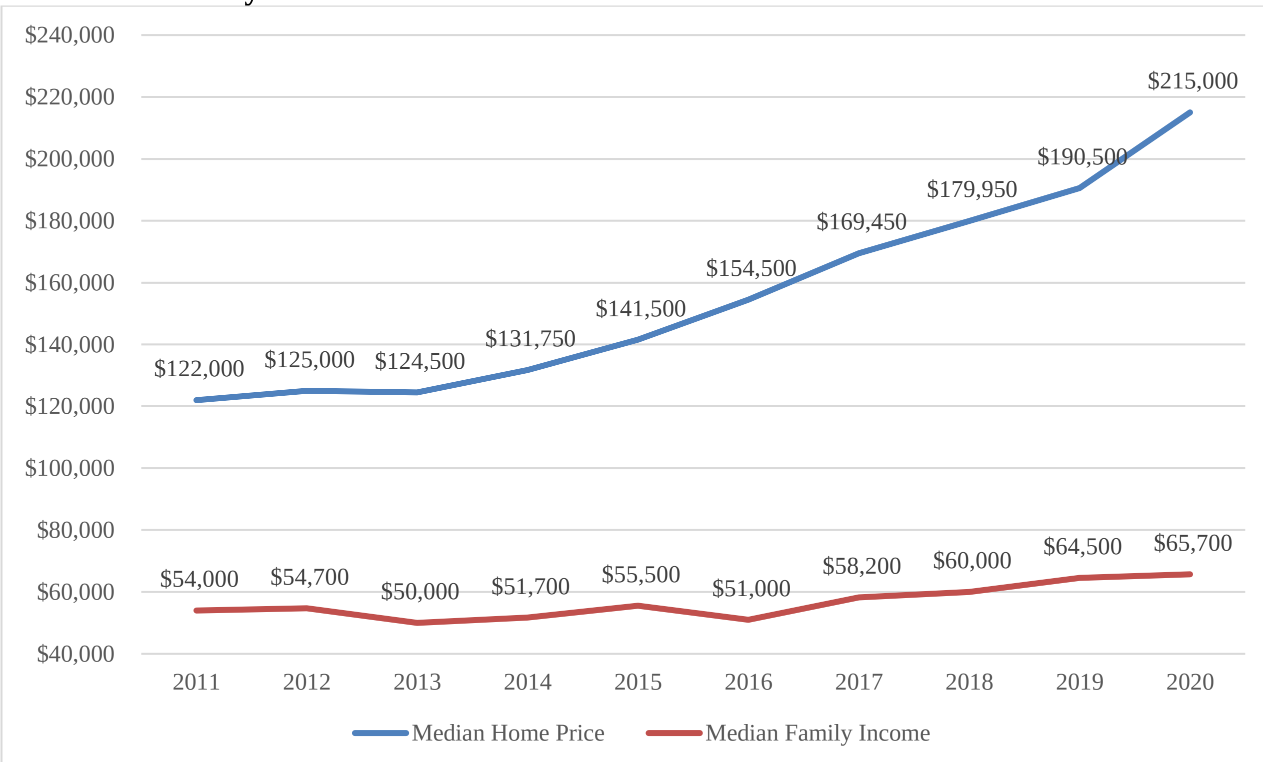
Source: HUD, Texas Real Estate Research Center

Figure 4.3 Comparison between Median Home Price and Median Family Income in the Austin-Round Rock MSA



Source: HUD, Texas Real Estate Research Center

Figure 4.4 Comparison between Median Home Price and Median Family Income in McLennan County



Source: HUD, Texas Real Estate Research Center

Secondary Data

This research relies solely on secondary data to address the research questions. Specifically, I use four sources of publicly-available secondary data. Table 4.3 lists the variables used for purchase affordability; Table 4.4, the variables used for neighborhood opportunity.

1) The Dynamic National Loan-Level Dataset, compiled under the Home Mortgage Disclosure Act (HMDA) and modified by the Consumer Financial Protection Bureau (CFPB). This data, published at the Census tract level, details the characteristics of

borrowers and loans originated in 2018 and 2019 for conventional, FHA-insured, VA-guaranteed, and RHS-guaranteed mortgages.

2) Price distributions of home sales in 2018 and 2019, published at the county level by the Texas Real Estate Research Center.

3) Income and home value distributions, published at the county and Census tract levels by the U.S. Census Bureau (American Community Survey).

4) Version 6 of the Affirmatively Furthering Fair Housing-Tool, published by the Department of Housing and Urban Development (HUD). This data, published at the Census tract or block group level, reflects seven Opportunity Indices designed to capture neighborhood opportunity.

Table 4.3 Description of Data for Purchase Affordability

Data Source	Type of Data	Variables
CFPB/HMDA	Home purchase mortgage originations	Loan characteristics: • Property value • LTV ratio • Interest rate • Rate spread • Loan term • Loan type (FHA, VA, or RHS) Borrower characteristics: • Income • DTI ratio • Race • Ethnicity • Sex • Age
Texas Real Estate Research Center	Home price	• Median home price • Home price distribution

Data Source	Type of Data	Variables
U.S. Census Bureau (American Community Survey)	Income & home value	• Household income distribution • Home value distribution

Table 4.4 Description of Data for Neighborhood Opportunity

HUD	AFFH	Opportunity Indices: • School Proficiency • Jobs Proximity • Environmental Health Hazards • Labor Market Engagement • Low Poverty • Transportation Costs • Transit Trips

Data Cleaning

The designated parameters of this research dictated cleaning of the CFPB/HMDA dataset. The filtering process for the CFPB/HMDA dataset follows sampling procedures largely utilized in previous research. Specifically, this research filters mortgage loans on six criteria: the 1) loan purpose, 2) occupancy type, 3) number of total units, 4) lien status, 5) construction method, and 6) action taken. Prior literature excludes all mortgage loans which are not designated for the purchase of owner-occupied properties with 1-4 units. This research only reflects first-lien mortgages to omit borrowers seeking piggyback loans (Faber, 2018; Haupert, 2019). Meanwhile, the scope of this research (mortgage *originations* for *site-built* homes) justifies the removal of 1) manufactured homes from the dataset and 2) loans which are not originated (i.e., applications, denials, etc.). Finally, this dataset includes only 1-unit properties; the proportion of 2-4 units proved particularly insubstantial in the least populous study site (Anderson County) and would have introduced unnecessary "noise" into the analysis.

Upon combining the data for 2018 and 2019, the initial CFPB/HMDA dataset contains 50,247,485 observations on mortgage loans across the United States and its territories. Table 4.3 details each criterion for filtering the data and the corresponding number of observations after applying that criterion. After filtering the data on the six aforementioned criteria and narrowing it to reflect only the three study sites, 117,263 observations remain.

Table 4.5 Number of Observations Corresponding to Each Filter

Criterion for Filter	**Observations Remaining**
+ Home purchase only (loan purpose == 1)	23,713,735
+ Owner-occupied only (occupancy_type == 1)	21,324,422
+ Single-family only (total_units == 1)	21,007,773
+ 1st-lien only (lien_status == 1)	20,407,230
+ Site-built only (construction_method == 1)	19,118,118
+ Originated only (action_taken == 1)	10,971,718
+ Nation to Texas	993,859
+ Texas to Study Sites	117,263

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

However, not all of those 117,263 observations offer complete data with respect to the variables used in this research. In fact, all eleven variables used from the CFPB/HMDA dataset contain between 121 and 19,204 missing observations. Missing data—which occurs when variables lack a value for a particular observation (or observations)—proves a particularly pervasive problem for researchers, nearly all of whom encounter missing data, regardless of research design. In the social sciences, one of the most ubiquitous causes of missing data includes nonresponse—incomplete questionnaires, surveys, and interviews (i.e., the respondent fails to answer all questions). With respect to secondary data, governments, businesses, nonprofit organizations, etc. may opt not to report certain observations, or the values for those observations may simply be unavailable (Bennett, 2001; Carpenter & Kenward, 2007; Scheffer, 2002).

If left untreated, missing data—depending on its nature and magnitude—may pose considerable concerns with respect to the validity of the researcher's results. Should the data be missing systematically, any statistical analysis that does not correct for the issue may diminish statistical power and produce biased results. However, should the data be missing randomly, the sample should be representative of the population (as such, results should not be biased) (Eekhout et al., 2012; Little & Rubin, 1989; Pigott, 2001). Table 4.6 lists the variables which present missing data and details the number of observations missing for each variable. Although generally small (i.e., inconsequential) for each variable, the number of missing observations for race and ethnicity—which accounts for over 16% of total observations—potentially poses methodological challenges.

Table 4.6 Tabulation of Missing Data in the CFPB/HMDA Dataset

Variable	Total Number of Missing Observations	Proportion of Missing Observations to Total Number of Observations	Total Number of Observations
Property value	2,985	2.5%	114,278
Interest rate	2,488	2.1%	114,775
Rate spread	3,776	3.2%	113,487
Loan term	2,523	2.2%	114,740
DTI ratio	3,338	2.8%	113,925
LTV ratio	5,125	4.4%	112,138
Income	647	0.6%	116,616
Race	19,204	16.4%	98,059
Ethnicity	19,030	16.2%	98,223
Sex	9,011	7.7%	108,252
Age	121	0.1%	117,142

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Several statistical techniques may correct for missing data. Listwise deletion—which involves the deletion of all observations containing at least one variable with missing data—constitutes the most commonly used method to address missing data, particularly in studies that involve HMDA data. It proves the most simplistic—and therefore problematic—among the array of techniques to address missing data (Kang, 2013; Myers, 2011). However, other techniques, including multiple imputation—generally considered one of the more rigorous techniques—did not produce results which differed in a statistically significant manner from those of listwise deletion. After applying listwise deletion to the CFPB/HMDA dataset, 88,313 (75.3%) of the initial observations remained.

Transforming and Recoding the Variables

This research made adjustments to nearly all variables in the CFPB/HMDA dataset to address issues with normality, measurement error, or the interpretation of its coefficients. Two variables—income and property value—presented skewed distributions. As such, this research uses the natural logarithm of both variables to improve normality. In the process of transforming income into its natural logarithm, 153 observations which equaled 0 were dropped. Another 22 observations with values of "999" for loan term were dropped. The final number of observations for this research totals 88,138 originated mortgages.

This research recoded six variables—the rate spread, LTV ratio, DTI ratio, and the race, ethnicity, and sex of the borrower—to facilitate the ease of interpretation of the coefficients. This research recoded rate spread (the variable high_cost) into a binary variable which equals 1 if the rate spread equals or exceeds 1.5%. Although the rate spread of the loan appears as a continuous variable in the dataset, it was recoded into a dichotomous variable for two reasons: 1) HMDA considers high-cost loans to be those for which the rate spread equals or exceeds 1.5% and 2) including rate spread as a continuous variable would distort the effect of the mortgage interest rate (*What Is a "higher-Priced Mortgage Loan?*, n.d.). The rate spread measures the difference between the loan's interest rate and the average mortgage interest rate (*HMDA Glossary*, n.d.). As such, including the rate spread as a continuous variable would erroneously inflate the mortgage interest rate.

Although originally a continuous variable, values for the LTV ratio—particularly with respect to federally-backed mortgages—tend to concentrate between 80% and 100%. Indeed, the LTV ratios for most federally-backed mortgages exceed 96.5%. Incorporating the LTV ratio as a continuous variable would present issues with normality. Instead, the LTV ratio was recoded into a categorical variable with six categories: 1) less than 80%, 2) 80-84.9%, 3) 85-89.9%, 4) 90-94.9%, 5) 95-99.9%, and 6) 100% and greater.

The DTI ratio, which appears as a categorical variable in the CFPB/HMDA dataset, was recoded into six categories: 1) less than 20%, 2) 20-<30%, 3) 30-39%, 4) 40-49%, 5) 50-60%, and 6) greater than 60%. In the initial dataset, the DTI ratio contains categories for variables less than 36% and equal to or greater than 50% and a continuous distribution for values between 36% and 49%, inclusive. Such an uneven distribution considerably obfuscates the interpretation of the coefficient.

Meanwhile, race originally contained over 15 categories in the CFPB/HMDA dataset—including the detailed race of Asian borrowers (i.e., Chinese, Filipino, etc.) and Native Hawaiian or Other Pacific Islander borrowers (i.e., Native Hawaiian, Samoan, etc.). It was recoded into four binary variables: white, black, Asian, and other. (Native American and Pacific Islander borrowers were not recoded into binary variables due to the small number of observations and are instead categorized as "other.") A value of 1 for white, black, Asian, or other indicates the borrower is white, black, Asian, or a race designated as "other," respectively. Ethnicity, which initially presented over eight categories in the CFPB/HMDA dataset, included detailed information on the ethnicity of Hispanic or Latino borrowers (i.e., Mexican, Puerto Rican, Cuban, etc.). It was recoded into a single binary variable, which equals 1 if the borrower is Hispanic or Latino. Sex was also recoded into a single binary variable, which equals 1 if the borrower is male. Lastly, no adjustments were made to the variable age. The categories for age include: 1) less than 25 years, 2) 25-34 years, 3) 35-44 years, 4) 45-54 years, 5) 55-64 years, 6) 65-74 years, and 7) greater than 75 years.

Methodology: HUD Opportunity Indexes

HUD developed seven Opportunity Indexes to reflect neighborhood opportunity: the Low Poverty, School Proficiency, Jobs Proximity, Labor Market Engagement, Transportation Costs, Transit Trips, and Environmental Health Hazards Indexes. Values for the indexes range from 0-100; higher values indicate higher opportunity. Based on Version 6 of the AFFH-T data, Table 4.7 provides a brief description of each index and lists the data sources used to compute the index and the geography represented by the index.

HUD operationalizes each Opportunity Index at one of two geographies: either the Census tract or block group level. The School Proficiency Index and Jobs Proximity Index denote the only two of seven indexes measured at the block group level. This section first describes the methodology used by HUD to produce each index, followed by a discussion on the methodology adopted in this research to aggregate the School Proficiency and Jobs Proximity Indexes to the Census tract level.

Table 4.7 Description of the HUD Opportunity Indexes

Name of Index	Description	Data Sources	Geography
Low Poverty Index	Reflects poverty, as measured by the poverty rate	American Community Survey, 2011-2015	Census tract
School Proficiency Index	Denotes school quality based on the performance of 4th grade students on state exams	Great Schools (proficiency data), 2016-17; Common Core of Data, 2016-17; Maponics School Attendance Zone database, 2018	Block group
Jobs Proximity Index	Depicts household demand for employment and the accompanying supply of jobs across a CBSA	Longitudinal Employer-Household Dynamics (LEHD), 2017	Block group
Labor Market Engagement Index	Reflects the supply of labor based on the unemployment rate, labor market participation rate, & the proportion of the population (25 years and older) with a bachelor's degree or higher	American Community Survey, 2011-2015	Census tract
Transportation Costs Index	Reflects the ratio of transportation costs to the income of renters	Location Affordability Index, 2012-2016	Census tract
Transit Trips Index	Depicts household access to public transit based on the	Location Affordability Index, 2012-2016	Census tract

Name of Index	Description	Data Sources	Geography
	number of annual transit trips		
Environmental Health Hazards Index	Measures potential exposure to toxins—air quality carcinogenic, respiratory, and neurological hazards—harmful to human health	National Air Toxics Assessment (NATA) data, 2014	Census tract

Source: HUD, (Gourevitch, 2018; Mast, 2015)

Low Poverty Index

The Low Poverty Index depicts poverty—as measured by the poverty rate—at the Census tract level. The 2011-2015 American Community Survey serves as the data source for the poverty rate. The index equals the poverty rate for a Census tract minus the average poverty rate for the United States, the difference of which is divided by the standard error of the national poverty rate. After taking the absolute value of the results, the figures are percentile ranked nationally, rendering values from 0 to 100. A higher score denotes a lower incidence of poverty in that Census tract (i.e., greater opportunity) (*AFFH-T Data Documentation*, 2020).

School Proficiency Index

The School Proficiency Index reflects the quality of the elementary schools most geographically proximate to a particular block group based on the performance of 4th grade students on state exams. Specifically, the index measures the proportion of 4th grade students with state test scores that demonstrate proficiency in reading and math. The index incorporates scores from students at a maximum of three schools within a three-mile radius of a particular block group. The index uses data from multiple sources, including 2016-2017 Great Schools data (for the state test scores of 4th grade students in reading and math), 2016-2017 Common Core of Data information (for the enrollment of 4th grade students and school addresses), and 2018 Pitney Bowes School Attendance Zone data (for mapping attendance boundaries) (*AFFH-T Data Documentation*, 2020; Mast, 2015).

The computation for the index is the sum of the number of 4th grade students within a particular school divided by the total number of 4th grade students enrolled in a maximum of three schools within a three-mile radius of the block group. This figure is multiplied by the sum of the percent of 4th grade students proficient in reading and the percent of 4th grade students proficient in math (the sum of which is divided by two). Finally, after taking the absolute value for each figure, the figures are percentile ranked nationally, rendering values from 0 to 100. A higher score indicates the presence of higher quality school(s) in that block group (i.e., greater opportunity) (*AFFH-T Data Documentation*, 2020).

The following steps describe the process of aggregating the School Proficiency Index to the Census tract level:

1) Multiply the number of 4th grade students by the School Proficiency Index for each block group.
2) Compute the sum of these values for each Census tract (i.e., add the values across all block groups within a tract to obtain the sum for the tract).
3) Compute the total number of 4th grade students within a Census tract (i.e., add the number of 4th grade students within each block group of a Census tract).

4) Divide the value obtained in step 2 by the value obtained in step 3 to reflect the School Proficiency Index for a particular Census tract.

Jobs Proximity Index

The jobs proximity index measures household demand for employment and the accompanying supply of jobs across a CBSA. Specifically, the index manifests accessibility as the distance from a particular block group to all centers of employment within a CBSA, applying greater weight to larger employment centers. The gravity model adopted to compute this index weighs the distance to all centers of employment by the ratio of the number of jobs in any single employment center to the labor force. The figures are percentile ranked at the CBSA level, rendering values from 0 to 100. A higher score indicates higher accessibility to jobs in that block group (i.e., greater opportunity). This index uses data from the 2017 Longitudinal Employer-Household Dynamics (LEHD) survey (*AFFH-T Data Documentation*, 2020).

The following steps describe the process of aggregating the Jobs Proximity Index to the Census tract level:

1) Multiply the number of individuals in the labor force by the Jobs Proximity Index for each block group.
2) Compute the sum of these values for each Census tract (i.e., add the values across all block groups within a tract to obtain the sum for the tract).
3) Compute the total number of individuals in the labor force within a Census tract (i.e., add the number of individuals in the labor force within each block group of a Census tract).

4) Divide the value obtained in step 2 by the value obtained in step 3 to reflect the Jobs Proximity Index for a Census tract.

Labor Market Engagement Index

The labor market engagement index, computed at the Census tract level, portrays the supply of labor based on the unemployment rate, labor force participation rate, and proportion of the population (25 years and older) with a bachelor's degree. Specifically, using 2011-2015 American Community Survey data, the index standardizes each of the three aforementioned variables by deducting the national average of that variable from its value for a particular Census tract and dividing it by the national standard error for that variable. The index equals the sum of the standardized scores for the three variables. The figures are percentile ranked nationally. A higher score indicates a higher supply of labor within a particular Census tract (*AFFH-T Data Documentation*, 2020).

Transportation Costs Index

The Transportation Costs Index uses 2012-2016 data from the Location Affordability Index to calculate estimates of transportation costs at the Census tract level for a three-person, single-parent family earning 50% of the area median income for renters. ("Area" consists of the entire CBSA.) This index reflects the ratio of transportation costs to the income of renters. Higher values for the index indicate lower transportation costs within a particular Census tract. Lower transportation costs could stem from higher accessibility to public transportation and/or higher accessibility to jobs, services, and amenities within the surrounding region (*AFFH-T Data Documentation*, 2020).

Transit Trips Index

Similar to the Transportation Costs Index, the Transit Trips Index uses 2012-2016 data from the Location Affordability Index to compute estimates of annual transit trips for a three-person, single-parent family earning 50% of the area median income for renters. ("Area" consists of the entire CBSA.) Higher values for the index suggest a greater propensity among residents within that Census tract to use public transit—likely the result of higher accessibility to public transit (*AFFH-T Data Documentation*, 2020).

Health Hazards Index

The Environmental Health Hazards Index uses data from the National Air Toxics Assessment (i.e., the Environmental Protection Agency) to capture, at the Census tract level, potential exposure to toxins—air quality carcinogenic, respiratory, and neurological hazards—harmful to human health. To compute the index, the national average of the estimate for a particular toxin is deducted from the estimate of that toxin for a given Census tract, which is divided by the national standard error for that estimate. The index equals the sum of the standardized scores for the three variables. A higher value for the Health Hazards Index indicates that residents of a particular Census tract face lower exposure to such toxins. In other words, neighborhoods with higher values for this index depict higher environmental quality (*AFFH-T Data Documentation*, 2020).

Data Analysis

This research uses cross-sectional data to assess the purchase affordability and neighborhood opportunity of four types of mortgage loans—conventional, FHA-insured, VA-guaranteed, and RHS-guaranteed—within three study sites. Specifically, this research consists of three stages: 1) developing an improved indicator of purchase affordability, 2) examining the relationship between purchase affordability and neighborhood opportunity, and 3) introducing a new framework by which to measure purchase affordability and neighborhood opportunity. The first and third stages involves empirical analysis; the second, structural equation modeling. Data analysis is conducted in Stata 16 and Carto, an online, freely accessible mapping platform.

Empirical Analysis

Through empirical analysis, this research develops an improved indicator of purchase affordability and a framework for planners, policymakers, and practitioners to measure purchase affordability and neighborhood opportunity. Chapters 6 and 8 describe in detail the methodology behind the derivation of the improved indicator and framework, respectively. Table 4.8 provides an overview of the variables used to develop the improved indicator of purchase affordability, while Table 4.9 lists the variables used to build the framework which models the interaction between purchase affordability and neighborhood opportunity.

Table 4.8 List of Variables Used in the Improved Indicator of Purchase Affordability

Dependent variable	Home price-to-income ratio (multiplier)
Independent variables	Property value
	Income

	Loan term
	Mortgage interest rate
	LTV ratio
	DTI ratio
	Property tax rate
	Property insurance rate
	Private mortgage insurance
	Upfront & annual mortgage insurance premium
	Funding fees

Table 4.9 List of Variables Used in the Framework of Purchase Affordability and Neighborhood Opportunity

Purchase affordability	Home price-to-income multiplier
Neighborhood opportunity	Low Poverty Index
	School Proficiency Index
	Jobs Proximity Index
	Labor Market Engagement Index
	Transportation Costs Index
	Transit Trips Index
	Environmental Health Hazards Index

Structural Equation Modeling (SEM)

This research uses confirmatory factor analysis (CFA)—specifically, a two-level measurement model, a statistical model which relates a person's status on observed variables to their status on latent variables, to examine the relationship between purchase affordability and neighborhood opportunity within the three study sites (Gallagher & Brown, 2013; Savalei & Bentler, 2010). Both purchase affordability and neighborhood opportunity represent latent constructs—neither can be explicitly derived, but can be manifested through an array of observed variables. In fact, as previously discussed, HUD operationalizes neighborhood opportunity through seven indexes. Common indicators of neighborhood opportunity include the poverty rate and racial composition of the neighborhood (Lens, 2017). Meanwhile, purchase affordability generally acts as a function of home price and household income, but may also include mortgage financing terms (Haurin, 2016).

This research adopts the seven Opportunity Indexes developed by HUD to reflect neighborhood opportunity. Meanwhile, it models purchase affordability as a function of home price and income as well as a variety of mortgage financing terms—the interest rate, rate spread (as depicted by the presence of a high-cost loan), LTV ratio, and DTI ratio. (The loan term is held constant at 30 years.) It also includes the loan type—whether FHA-insured, VA-guaranteed, or RHS-guaranteed. Moreover, the CFA controls for the borrower’s race, ethnicity, sex, and age. Table 4.10 provides an overview of the latent and observed variables used in the CFA.

Table 4.10 List of Variables Used in the Confirmatory Factor Analysis

Latent Construct	Purchase Affordability	Neighborhood Opportunity
Observed Variables	Property value	Low Poverty Index
	Income	School Proficiency Index
	LTV ratio	Jobs Proximity Index
	DTI ratio	Labor Market Engagement Index
	Interest rate	Transportation Costs Index
	High cost	Transit Trips Index
	FHA	Environmental Health Hazards Index
	VA	
	RHS	
Control Variables	White	
	Black	
	Asian	
	Hispanic	
	Male	
	Age	

Study Limitations

This research suffers from two primary limitations: endogeneity and issues with the data. This section provides a brief overview of these limitations, which will be discussed more in-depth in future chapters.

A Note on Endogeneity

Modeling purchase affordability and neighborhood opportunity poses several methodological challenges with respect to endogeneity. Establishing causality proves foundational to research in the social sciences. However, endogeneity—in its myriad of forms—generally poses several challenges to achieving causality, particularly for researchers unable to perform random experiments, commonly seen as the "gold standard." Causality requires that the error, or disturbance, terms remain independent of the explanatory variables (i.e., the independent variables). Endogeneity, which appears when the independent variables and error terms are jointly determined, may present itself in a variety of forms, including selection bias, measurement error, omitted variables, simultaneity, and common method variance (Antonakis et al., 2010; Ghose, 2019). In this research, endogeneity appears in three forms: measurement error, omitted variables, and simultaneity.

The first issue, measurement error, appears in the CFPB/HMDA data. For instance, 22 observations for loan term are coded "999." Mortgage lenders are quite obviously not originating loans for a duration of over 83 years; rather, "999" indicates a coding error. While these incidences of measurement error are fairly easy to recognize, there is also the potential for measurement error that is more difficult to discern. For instance, a mortgage lender accidentally coding an applicant as male instead of female, incorrectly recording the property value (i.e., $50,000 instead of $500,000), etc.

The second issue, omitted variables, presents itself most evidently in the absence of data on the credit scores of borrowers. One of the three primary borrowing constraints, credit scores play a crucial role in determining purchase affordability (Acolin, Bricker, et al., 2016). The third issue, simultaneity, presents itself in the relationship between purchase affordability and neighborhood opportunity. It is difficult to disentangle the two from each other with respect to timing/sequencing—i.e., purchase affordability and neighborhood opportunity are decided simultaneously; neither precedes the other.

Data Limitations

The CFPB/HMDA data does not reflect <u>all</u> mortgage originations; HMDA and its amendments mandate only certain financial and non-financial institutions to report data on mortgage originations. Furthermore, although required to report particular characteristics, certain financial and non-financial institutions may be able to exempt themselves from reporting other characteristics. Meanwhile, home sales data compiled and published by the Texas Real Estate Research Center reflects only those homes sold through the Multiple Listing Service (MLS), a central repository of data on homes currently for sale or recently sold that is primarily used by realtors and appraisers to locate properties for homebuyers or execute a comprehensive search on comparable properties to include in appraisal reports. The MLS disproportionately underrepresents home sales in lower-priced cohorts (i.e., homes more likely to be sold to low-income households), as homes in lower-priced cohorts bear a higher probability of being listed and sold by individual sellers (i.e., sold by the owner as opposed to a realtor). Such transactions would fail to be recorded in the MLS.

Although published in July 2020, each of the seven individual indexes uses data compiled over, in particular instances, several years. This could reduce the ability of those indexes to generalize to contemporaneous circumstances. However, since the Opportunity Index measures structural characteristics of neighborhoods, as opposed to—for example—demographic characteristics, these characteristics should be more resistant to fleeting change, such as would occur over a several-year span. Finally, the home value distribution published by the U.S. Census Bureau (American Community Survey) does not denote the sales price of the home, but rather, the value the owner believes the house to be worth (*Why We Ask About... Ownership, Home Value, and Rent*, n.d.).

CHAPTER V

DATA ANALYSIS

Purchase affordability and neighborhood opportunity denote convoluted concepts comprised of a myriad of underlying variables (Dokko, 2018; Knaap, 2017; Lens, 2017; Quigley & Raphael, 2004). Measuring the two concepts, both individually and conjointly, first requires comprehension of the nature of these variables, which differ considerably both with respect to 1) the type of mortgage originated (i.e., conventional, FHA-insured, VA-guaranteed, or RHS-guaranteed) and 2) the characteristics of the borrower, loan, and neighborhood (Baeck & DeVaney, 2003; Pennington-Cross & Nichols, 2000). Such disparities stem from variations in borrowing constraints, the eligibility requirements dictated by the four types of mortgages, and regional effects, such as the strength of the local economy and housing market (Acolin, Bricker, et al., 2016; Follain, 1990a; Linneman & Wachter, 1989). Through summary statistics and maps, this chapter provides a comprehensive overview of the characteristics of borrowers, loans, and neighborhoods for conventional, FHA-insured, VA-guaranteed, and RHS-guaranteed mortgages.

Characteristics of Borrowers

Income

Borrower income deviates considerably among the four loan types—to the magnitude of tens of thousands of dollars within each study site (see Tables 5.1-5.6). On average, across the three study sites, mean income ranks the highest among borrowers with conventional mortgages and the lowest among borrowers with RHS-guaranteed mortgages. The former phenomenon originates from the more stringent standards (with respect to income, wealth, and credit) imposed on borrowers who obtain conventional mortgage financing versus those who seek government-insured mortgages (Baeck & DeVaney, 2003; Getter, 2021; Jones, 2018; McCarty et al., 2019). Meanwhile, the latter phenomenon likely stems from the eligibility requirements of RHS-guaranteed mortgages: firstly, the property must be located in a “rural” area, and households in rural communities generally present lower incomes than households in urban areas, and secondly, the borrower’s income typically must fall between 80% and 115% of the area median income (Foote, 2010a; Scally & Lipsetz, 2017).

Moreover, among all four loan types, mean borrower income measures the highest in the Austin-Round Rock MSA and the lowest in Anderson County. This stems from higher housing costs and incomes in the former. The mean income of FHA-insured borrowers falls below that of VA-guaranteed borrowers, which could be a function of the greater age of VA-guaranteed borrowers, who may be further along in the employment cycle and therefore more likely to be of higher income (Foote, 2010b; Goodman et al., 2014; Perl, 2017).

Table 5.1 Summary Statistics for Income in Anderson County (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	$77,460	$60,707	$81,336	$51,351
Median	$81,000	$61,000	$74,000	$49,960
Standard Deviation	$1,879	$1,566	$1,699	$1,319

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.2 Summary Statistics for Income in Anderson County (2019)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	$82,438	$61,244	$73,733	$50,435
Median	$80,000	$67,993	$69,000	$52,000

Standard Deviation	$1,746	$1,525	$1,756	$1,329

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.3 Summary Statistics for Income in the Austin-Round Rock MSA (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	$115,982	$78,876	$94,066	$70,611
Median	$113,000	$78,000	$92,000	$72,000
Standard Deviation	$1,812	$1,523	$1,576	$1,251

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.4 Summary Statistics for Income in the Austin-Round Rock MSA (2019)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	$120,107	$81,614	$96,541	$75,258
Median	$118,000	$81,000	$95,000	$77,000
Standard Deviation	$1,829	$1,501	$1,552	$1,227

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.5 Summary Statistics for Income in McLennan County (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	$80,950	$65,004	$79,531	$53,801
Median	$81,000	$66,000	$79,000	$56,498
Standard Deviation	$1,848	$1,554	$1,551	$1,319

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.6 Summary Statistics for Income in McLennan County (2019)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	$88,376	$65,933	$80,935	$55,196
Median	$87,000	$68,000	$79,498	$56,498
Standard Deviation	$1,891	$1,744	$1,641	$1,233

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

The median DTI ratio for FHA-insured and VA-guaranteed mortgages generally measures higher than that of conventional and RHS-guaranteed mortgages (see Tables 5.7-5.12). With the exception of Anderson County in 2018, the median DTI ratio for FHA-insured and VA-guaranteed mortgages ranges from 40% to 49%, whereas the median DTI ratio for conventional and RHS-guaranteed mortgages falls between 30% and 39%. This suggests that borrowers who obtain FHA or VA mortgage financing in the three study sites exhibit, on average, a higher level of indebtedness than borrowers who obtain conventional or RHS mortgage financing.

Across all three study sites and loan types, only a small percentage of borrowers present DTI ratios less than 20% or greater than 60%. (Among the four loan types, conventional loans depict the highest proportion of borrowers with DTI ratios less than 20%—ranging from 4.7% to 8.4% of borrowers with conventional loans, while VA-guaranteed loans portray the highest proportion of borrowers with DTI ratios greater than 60%—up to 5% of borrowers with VA-guaranteed mortgages.) Moreover, borrowers in Anderson County presented a lower mean DTI ratio than borrowers in McLennan County or the Austin-Round Rock MSA.

Table 5.7 Distribution of Borrowers by DTI Ratio in Anderson County (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
<20%	6.9%	1.5%		
20-29%	26.7%	10.6%	40%	40.9%
30-39%	38.2%	31.8%	13.3%	54.5%
40-49%	26%	36.4%	40%	4.5%
50-60%	2.3%	19.7%	6.7%	

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.8 Distribution of Borrowers by DTI Ratio in Anderson County (2019)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
<20%	8.4%	2.9%		5.9%
20-29%	18.9%	11.4%	12.9%	17.6%

30-39%	39.2%	34.3%	35.5%	47.1%
40-49%	32.2%	27.1%	25.8%	29.4%
50-60%	0.7%	24.3%	22.6%	
>60%	0.7%		3.2%	

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.9 Distribution of Borrowers by DTI Ratio in the Austin-Round Rock MSA (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
<20%	4.7%	0.5%	1.5%	1.2%
20-29%	19.7%	4.5%	7.3%	5.5%
30-39%	34.8%	17.3%	23.7%	58.5%
40-49%	39.6%	40.2%	36.2%	34.3%
50-60%	0.8%	36.4%	26.7%	
>60%	0.3%	1.1%	4.6%	0.5%

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.10 Distribution of Borrowers by DTI Ratio in the Austin-Round Rock MSA (2019)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
<20%	6.1%	0.5%	1.8%	0.3%
20-29%	22%	4.7%	9.9%	8.7%
30-39%	35%	20.5%	24.1%	50.5%
40-49%	35.8%	38.9%	35.1%	40.5%
50-60%	0.9%	35.3%	24.1%	
>60%	0.2%	0.1%	5%	

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.11 Distribution of Borrowers by DTI Ratio in McLennan County (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
<20%	6.6%	0.5%	0.8%	
20-29%	20.2%	6.7%	9%	17.6%
30-39%	34.7%	21.4%	26.6%	61.8%
40-49%	37.7%	37.8%	35.7%	20.6%
50-60%	0.4%	33.4%	23.8%	
>60%	0.4%	0.2%	4.1%	

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.12 Distribution of Borrowers by DTI Ratio in McLennan County (2019)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
<20%	7%	0.8%	1.8%	

20-29%	22.9%	8.3%	9.2%	12.5%
30-39%	34.2%	23.1%	27.9%	54.2%
40-49%	34.9%	43.3%	39%	33.3%
50-60%	0.6%	24.6%	19.5%	
>60%	0.4%		2.6%	

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Race & Ethnicity

White, non-Hispanic or Latino households comprise the vast majority of borrowers among all four loan types (see Tables 5.13-5.18). However, the proportion of such borrowers varies considerably with respect to the loan type and the study site. Overall, Anderson County contains the highest proportion of white, non-Hispanic or Latino borrowers, who accounted for 78.6% and 78.2% of all borrowers in 2018 and 2019, respectively. In McLennan County, white, non-Hispanic or Latino borrowers represented over three-quarters of all borrowers (76.1% in 2018 and 76.6% in 2019). Meanwhile, in the Austin-Round Rock MSA, white, non-Hispanic or Latino borrowers constituted slightly over two-thirds of all borrowers (67.4% in 2018 and 67.5% in 2019).

In the Austin-Round Rock MSA and McLennan County, conventional loans depict the highest proportion of white, non-Hispanic or Latino borrowers—who represented over 70% and 80% of all borrowers in the Austin-Round Rock MSA and McLennan County, respectively. Meanwhile, in Anderson County, VA-guaranteed mortgages portray a slightly share of white, non-Hispanic or Latino borrowers than conventional mortgages. In the Austin-Round Rock MSA, the proportion of such borrowers proves the lowest among FHA-insured borrowers; however, in Anderson County and McLennan County, RHS-guaranteed mortgages generally depict the lowest share of white, non-Hispanic or Latino borrowers.

Table 5.13 Distribution of Borrowers by Race/Ethnicity and Loan Type in Anderson County (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
White (non-Hispanic or Latino)	83.2%	69.7%	93.3%	68.2%
Hispanic or Latino	6.1%	15.2%	6.7%	13.6%
Black or African American (non-Hispanic or Latino)	9.2%	13.6%		18.2%
Asian (non-Hispanic or Latino)	0.8%	1.5%		
Other	0.8%			

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.14 Distribution of Borrowers by Race/Ethnicity and Loan Type in Anderson County (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
White (non-Hispanic or Latino)	81.8%	72.9%	83.9%	58.8%
Hispanic or Latino	8.4%	12.9%	9.7%	29.4%
Black or African American (non-Hispanic or Latino)	6.3%	11.4%	6.5%	11.8%
Asian (non-Hispanic or Latino)	2.1%			
Other	1.4%	2.9%		

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.15 Distribution of Borrowers by Race/Ethnicity and Loan Type in the Austin Round-Rock MSA (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
White (non-Hispanic or Latino)	71.4%	49.3%	66.4%	53.2%
Hispanic or Latino	12.7%	37%	18.8%	34.1%
Black or African American (non-Hispanic or Latino)	2.4%	9.3%	11%	10.6%
Asian (non-Hispanic or Latino)	12.9%	3.6%	2.6%	1.8%
Other	0.6%	0.8%	1.2%	0.2%

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.16 Distribution of Borrowers by Race/Ethnicity and Loan Type in the Austin Round-Rock MSA (2019)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
White (non-Hispanic or Latino)	71.1%	50.1%	66.1%	55.9%
Hispanic or Latino	13%	34.9%	19%	32.1%
Black or African American (non-Hispanic or Latino)	2.5%	10.6%	10.9%	9.9%
Asian (non-Hispanic or Latino)	13%	3.6%	2.9%	1.2%
Other	0.5%	0.8%	1.1%	0.9%

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.17 Distribution of Borrowers by Race/Ethnicity and Loan Type in McLennan County (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
White (non-Hispanic or Latino)	82.3%	63.6%	73.8%	61.8%
Hispanic or Latino	11.8%	22.4%	12.3%	26.5%
Black or African American (non-Hispanic or Latino)	3%	12.4%	11.9%	11.8%
Asian (non-Hispanic or Latino)	2.7%	0.9%	0.8%	
Other	0.3%	0.7%	1.2%	

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.18 Distribution of Borrowers by Race/Ethnicity and Loan Type in McLennan County (2019)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
White (non-Hispanic or Latino)	81.5%	66.4%	74.6%	75%
Hispanic or Latino	11.4%	20.0%	12.5%	16.7%
Black or African American (non-Hispanic or Latino)	3.3%	12.5%	10.7%	8.3%

Asian (non-Hispanic or Latino)	3.0%	0.8%	1.1%	
Other	0.7%	0.4%	1.1%	

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Sex

Males comprise the overwhelming majority of borrowers among all loan types and study sites (see Tables 5.19-5.24). VA-guaranteed mortgages present the highest share of male borrowers, which range from 82.4% to 87.1%, a function of the eligibility requirements of VA-guaranteed mortgages (i.e., the VA extends mortgage financing solely to Servicemembers, Veterans, Reservists, National Guard members, and surviving spouses) (Foote, 2010b; Perl, 2017). FHA-insured and RHS-guaranteed mortgages portray the lowest share of male borrowers.

Table 5.19 Distribution of Borrowers by Sex and Loan Type in Anderson County (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Male	74.8%	66.7%	86.7%	68.2%
Female	25.2%	33.3%	13.3%	31.8%

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.20 Distribution of Borrowers by Sex and Loan Type in Anderson County (2019)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Male	72.7%	67.1%	87.1%	70.6%
Female	27.3%	32.9%	12.9%	29.4%

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.21 Distribution of Borrowers by Sex and Loan Type in the Austin-Round Rock MSA (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Male	68.2%	62%	87%	57.6%
Female	31.8%	38%	13%	42.4%

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.22 Distribution of Borrowers by Sex and Loan Type in the Austin-Round Rock MSA (2019)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Male	66.2%	57.9%	84.1%	60.1%
Female	33.8%	42.1%	15.9%	39.9%

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.23 Distribution of Borrowers by Sex and Loan Type in McLennan County (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Male	66.2%	62.2%	82.4%	67.6%
Female	33.8%	37.8%	17.6%	32.4%

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.24 Distribution of Borrowers by Sex and Loan Type in McLennan County (2019)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Male	64.8%	54.1%	87.1%	50%
Female	35.2%	45.9%	12.9%	50%

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Age

The highest proportion of borrowers generally falls in the 25-44 age categories, particularly for borrowers with FHA-insured loans, which seek to extend mortgage credit to first-time homebuyers (see Tables 5.25-5.30). Across all three study sites, borrowers with FHA-insured and RHS-guaranteed loans are slightly younger, on average, than borrowers with conventional and VA-guaranteed loans. The mean age of borrowers with FHA-insured and RHS-guaranteed loans hovers between 25 and 34 years old, while the mean age of borrowers with conventional and VA-guaranteed loans measures between 35 and 44 years old (with the exception of borrowers with VA-guaranteed loans in Anderson County in 2018, for whom the mean age ranged from 45 to 54 years).

Table 5.25 Distribution of Borrowers by Age and Loan Type in Anderson County (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
<25	3.8%	15.2%		9.1%
25-34	22.9%	28.8%	13.3%	54.5%
35-44	22.1%	33.3%	20.0%	18.2%
45-54	16.0%	12.1%	33.3%	9.1%
55-64	19.8%	6.1%	6.7%	
65-74	12.2%	3%	13.3%	9.1%
>75	3.1%	1.5%	13.3%	

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.26 Distribution of Borrowers by Age and Loan Type in Anderson County (2019)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
<25	4.9%	5.7%	6.5%	41.2%
25-34	19.6%	41.4%	19.4%	29.4%
35-44	22.4%	28.6%	16.1%	17.6%
45-54	24.5%	14.3%	29.0%	5.9%
55-64	16.1%	7.1%	6.5%	5.9%
65-74	10.5%	3%	12.9%	
>75	2.1%		9.7%	

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.27 Distribution of Borrowers by Age and Loan Type in the Austin-Round Rock MSA (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
<25	2.8%	5.8%	1.6%	9.7%
25-34	34.8%	41.5%	29%	51.6%
35-44	30.1%	28.9%	27.8%	20.3%
45-54	16.6%	15.9%	21.7%	10.1%
55-64	9.5%	6.3%	9.7%	7.1%
65-74	5.1%	1.4%	8.5%	1.2%
>75	1%	0.2%	1.7%	

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.28 Distribution of Borrowers by Age and Loan Type in the Austin-Round Rock MSA (2019)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
<25	2.9%	6.7%	2.1%	8.7%
25-34	35.1%	39.0%	30.4%	54.4%

35-44	29.8%	28.4%	27.8%	18.6%
45-54	16.3%	17.2%	19.6%	12.6%
55-64	9.7%	6.9%	10.3%	3.6%
65-74	5.0%	1.6%	7.8%	1.8%
>75	1.2%	0.2%	1.9%	0.3%

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.29 Distribution of Borrowers by Age and Loan Type in McLennan County (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
<25	6.5%	12.7%	1.2%	20.6%
25-34	33.4%	40.8%	26.6%	35.3%
35-44	24.6%	20.5%	22.5%	26.5%
45-54	13.7%	14.1%	20.9%	11.8%
55-64	14.4%	8.8%	13.1%	2.9%
65-74	5.8%	2.8%	12.7%	2.9%
>75	1.7%	0.5%	2.9%	

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.30 Distribution of Borrowers by Age and Loan Type in McLennan County (2019)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
<25	6.3%	8.9%	1.5%	16.7%
25-34	30.7%	40.1%	24.3%	37.5%
35-44	27.1%	23.6%	22.4%	16.7%
45-54	15.8%	17.0%	20.6%	12.5%
55-64	10.7%	8.5%	12.5%	12.5%
65-74	7.5%	1.3%	15.1%	
>75	1.9%	0.6%	3.7%	4.2%

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Characteristics of Loans

With respect to the three study sites, the Austin-Round Rock MSA represents the vast majority of mortgage originations in both 2018 and 2019—92.8% and 92.4%, respectively (see Table 5.31). Conventional loans comprise the majority of loan originations in all three study sites (73.9% and 74.8% of total originations in 2018 and 2019, respectively), but especially in the

Austin-Round Rock MSA, in which conventional loans represented over three-quarters of total originations in 2018 and 2019 (see Tables 5.32-5.34). FHA-insured loans compose over one-fourth of mortgage originations in both Anderson and McLennan County in 2018 and 2019. The proportion of VA-guaranteed mortgages ranks the highest in McLennan County—over 13% in McLennan County compared to over 8% in the Austin-Round Rock MSA. McLennan County borders Coryell County (home to Ford Hood, a large military base). RHS-guaranteed mortgages constitute a particularly small proportion of total originations in McLennan County and the Austin-Round Rock MSA (between 1% and 2%), but a more substantial share of total originations in Anderson County (9.4% in 2018 and 6.5% in 2019).

Table 5.31 Distribution of Mortgages by Loan Type

	2018	2019
Conventional	20,425 (73.9%)	45,238 (74.8%)
FHA-Insured	4,298 (15.6%)	9,142 (15.1%)
VA-Guaranteed	2,421 (8.8%)	5,376 (8.9%)
RHS-Guaranteed	490 (1.8%)	748 (1.2%)
Total	27,634	60,504

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.32 Distribution of Mortgages by Loan Type in Anderson County

	2018	2019
Conventional	131 (56%)	286 (54.8%)
FHA-Insured	66 (28.2%)	140 (26.8%)
VA-Guaranteed	15 (6.4%)	62 (11.9%)
RHS-Guaranteed	22 (9.4%)	34 (6.5%)
Total	234	522

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.33 Distribution of Mortgages by Loan Type in the Austin-Round Rock MSA

	2018	2019
Conventional	19,240 (75.1%)	42,514 (76.1%)
FHA-Insured	3,798 (14.8%)	7,944 (14.2%)
VA-Guaranteed	2,162 (8.4%)	4,770 (8.5%)
RHS-Guaranteed	434 (1.7%)	666 (1.2%)
Total	25,634	55,894

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.34 Distribution of Mortgages by Loan Type in McLennan County

	2018	2019
Conventional	1,054 (59.7%)	2,438 (59.6%)
FHA-Insured	434 (24.6%)	1,058 (25.9%)
VA-Guaranteed	244 (13.8%)	544 (13.3%)
RHS-Guaranteed	34 (1.9%)	48 (1.2%)
Total	1,766	4,088

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Property Value

The median property value varies widely across the three study sites (see Tables 5.35 – 5.40). In the Austin-Round Rock MSA, the mean property value of conventional mortgages ranks higher than that of any other loan type. However, in Anderson and McLennan Counties, the mean property values of conventional and VA-guaranteed mortgages approximate each other, with the mean property value of VA-guaranteed mortgages actually higher than that of conventional mortgages. The mean property value of RHS-guaranteed mortgages proves the lowest among all four loan types, largely a function of the geographic limitations imposed on properties purchased by borrowers with RHS-guaranteed mortgages.

Table 5.35 Summary Statistics for Property Value in Anderson County (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	$168,500	$136,282	$151,709	$109,966
Median	$165,000	$135,000	$135,000	$99,875
Standard Deviation	$1.8	$1.5	$1.8	$1.3

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.36 Summary Statistics for Property Value in Anderson County (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	$188,392	$141,090	$192,631	$105,674
Median	$185,000	$145,000	$185,000	$105,000
Standard Deviation	$1.7	$1.4	$1.6	$1.3

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.37 Summary Statistics for Property Value in the Austin-Round Rock MSA (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	$368,019	$243,933	$300,490	$208,189
Median	$345,000	$235,000	$284,999	$214,999
Standard Deviation	$1.6	$1.3	$1.4	$1.2

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.38 Summary Statistics for Property Value in the Austin-Round Rock MSA (2019)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	$381,181	$253,227	$308,430	$226,885
Median	$354,999	$244,999	$295,000	$225,001
Standard Deviation	$1.6	$1.3	$1.4	$1.2

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.39 Summary Statistics for Property Value in McLennan County (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	$207,438	$162,781	$220,499	$143,102
Median	$205,001	$165,000	$219,942	$155,000
Standard Deviation	$1.7	$1.4	$1.5	$1.3

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.40 Summary Statistics for Property Value in McLennan County (2019)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	$231,809	$172,286	$234,507	$151,695
Median	$225,001	$175,000	$235,000	$149,916

Standard Deviation	$1.6	$1.4	$1.5	$1.3

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Loan-to-Value (LTV) Ratio

With respect to the three study sites, conventional loans consistently depict the lowest average LTV ratios (slightly more than 80%) (see Tables 5.41-5.46). Conversely, the average LTV ratios of RHS-guaranteed mortgages generally prove the highest—a function of its structure. Within Anderson County and the Austin-Round Rock MSA, the average LTV ratios for FHA-insured and VA-guaranteed deviate only very slightly from each other.

Table 5.41 Summary Statistics for LTV Ratio in Anderson County (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	81.8%	96.5%	95.4%	100%
Median	85.0%	96.7%	100%	100.4%
Standard Deviation	15.3%	3.8%	11.3%	1.9%

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.42 Summary Statistics for LTV Ratio in Anderson County (2019)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	81.9%	96.3%	96.5%	99%
Median	80%	96.5%	100%	99.6%
Standard Deviation	13.8%	1.3%	9.3%	1.8%

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.43 Summary Statistics for LTV Ratio in the Austin-Round Rock MSA (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	81.3%	96.3%	96.4%	99.7%
Median	80%	96.5%	100%	100.5%

Standard Deviation	15.0%	4.8%	20.3%	3.3%

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.44 Summary Statistics for LTV Ratio in the Austin-Round Rock MSA (2019)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	81.6%	95.9%	96%	99.7%
Median	80%	96.5%	100%	100.2%
Standard Deviation	15.1%	5.5%	9.9%	2.5%

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.45 Summary Statistics for LTV Ratio in McLennan County (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	83.4%	95.6%	97.5%	97.3%
Median	85.1%	96.5%	100%	99.9%
Standard Deviation	15.1%	5.2%	7.5%	7.6%

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.46 Summary Statistics for LTV Ratio in McLennan County (2019)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	83.6%	95.9%	97.6%	99.4%
Median	86%	96.5%	100%	100.4%
Standard Deviation	14.5%	5.5%	7.5%	2.4%

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Interest Rate

Overall, the mortgage interest rate does not vary substantially among loan types and study sites, with the average and median rates generally measuring between 4.0% and 5.0% (see Tables 5.47-5.52). FHA-insured mortgages broadly depict the highest average interest rate, likely a function of the greater risk posed by such borrowers (i.e., nationwide, the FHA serves as the primary purveyor of mortgage financing to first-time buyers, who tend to be of lower income, wealth, and credit than repeat buyers).

Table 5.47 Summary Statistics for Interest Rate in Anderson County (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	4.9%	5.2%	4.7%	5%
Median	4.9%	5.1%	4.9%	5%
Standard Deviation	0.7%	0.6%	0.5%	0.4%

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.48 Summary Statistics for Interest Rate in Anderson County (2019)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	4.6%	4.6%	4.4%	4.4%
Median	4.5%	4.6%	4.3%	4.5%
Standard Deviation	0.8%	0.6%	0.7%	0.4%

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.49 Summary Statistics for Interest Rate in the Austin-Round Rock MSA (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	4.6%	4.9%	4.5%	4.7%
Median	4.6%	4.9%	4.5%	4.8%
Standard Deviation	0.5%	0.6%	0.5%	0.4%

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.50 Summary Statistics for Interest Rate in the Austin-Round Rock MSA (2019)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	4.1%	4.3%	3.9%	4%
Median	4%	4.3%	3.9%	4%
Standard Deviation	0.6%	0.7%	0.6%	0.5%

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.51 Summary Statistics for Interest Rate in McLennan County (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	4.8%	5.1%	4.5%	5.1%
Median	4.8%	5.1%	4.5%	5.1%
Standard Deviation	0.6%	0.5%	0.6%	0.3%

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.52 Summary Statistics for Interest Rate in McLennan County (2019)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	4.3%	4.6%	4.1%	4%
Median	4.3%	4.6%	4%	4.1%
Standard Deviation	0.6%	0.7%	0.7%	0.4%

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Loan Term

The average and median loan term do not deviate considerably among loan types and study sites, but particularly vary little among the federally-backed mortgages (see Tables 5.53 – 5.58). As exemplified by the standard deviation (i.e., the lack thereof), all RHS-guaranteed mortgages in this dataset were originated for 30-year terms.

Table 5.53 Summary Statistics for Loan Term in Anderson County (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	324	360	360	360
Median	360	360	360	360
Standard Deviation	72	1	0	0

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.54 Summary Statistics for Loan Term in Anderson County (2019)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	335	357	354	360
Median	360	360	360	360
Standard Deviation	63	20	32	0

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.55 Summary Statistics for Loan Term in the Austin-Round Rock MSA (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	346	360	358	360
Median	360	360	360	360
Standard Deviation	48	5	16	0

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.56 Summary Statistics for Loan Term in the Austin-Round Rock MSA (2019)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	347	360	359	360
Median	360	360	360	360
Standard Deviation	47	8	14	0

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.57 Summary Statistics for Loan Term in McLennan County (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	337	359	356	360
Median	360	360	360	360
Standard Deviation	64	12	27	0

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.58 Summary Statistics for Loan Term in McLennan County (2019)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Mean	342	359	358	360
Median	360	360	360	360
Standard Deviation	56	15	18	0

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

High Cost

Among all study sites, a substantial proportion of borrowers of FHA-insured mortgages receive high-cost loans—loans for which the rate spread exceeds 1.5%—with averages ranging from 37.7% to 66.7% (see Tables 5.59 and 5.60). (In other words, in 2019, high-cost loans comprised 58.6% of all loans originated to borrowers of FHA-insured mortgages.) Meanwhile, the share of high-cost loans among conventional borrowers proves considerably lower—the highest such proportion measures 21%. A very low percentage of borrowers of VA-guaranteed and RHS-guaranteed mortgages obtain high-cost loans. Anderson County houses the highest concentration of high-cost loans, followed by McLennan County.

Table 5.59 Distribution of High-Cost Loans by Loan Type (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Anderson County	16%	66.7%	0%	13.6%
Austin-Round Rock MSA	2.4%	40.4%	0.4%	0.7%
McLennan County	10.1%	56.2%	0.8%	0%

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 5.60 Distribution of High-Cost Loans by Loan Type (2019)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Anderson County	21%	58.6%	12.9%	0%
Austin-Round Rock MSA	2.8%	37.7%	1.6%	0%
McLennan County	8.1%	54.6%	4.8%	0%

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Characteristics of Neighborhoods

The summary statistics for the seven opportunity indexes reveal two key phenomena (see Tables 5.61-5.63). Firstly, on average, the Austin-Round Rock MSA boosts the highest opportunity, outranking Anderson and McLennan Counties, while Anderson County portrays the lowest opportunity. Secondly, on average, each index in Anderson County depicts the lowest variance among the three geographies; the Austin-Round Rock MSA, the highest. This suggests that the Austin-Round Rock MSA contains the most disparities in neighborhood opportunity; Anderson County, the least. It is perhaps not surprising that a more populous geography presents more differentiation with respect to opportunity.

In Anderson County, the Transportation Costs and Transit Trips Indexes present the lowest opportunity; the Jobs Proximity and Health Hazards Indexes, the highest. Likewise, in McLennan County, the Transportation Costs and Transit Trips Indexes contain the lowest opportunity. However, the School Proficiency and Labor Market Engagement Indexes prove highest in McLennan County. Within the Austin-Round Rock MSA, the Jobs Proximity Index depicts the lowest opportunity; the Labor Market Engagement and Low Poverty Indexes, the highest.

Opportunity Indexes

Table 5.61 Summary Statistics for Opportunity Indexes in Anderson County

	Mean	Median	Minimum	Maximum	Standard Deviation
Jobs Proximity Index	51.5	51.9	2	87.5	23
School Proficiency Index	36.2	22.3	18	84	24.5
Labor Market Engagement Index	46.4	47	0	75	19.3
Environmental Health Hazards Index	51.9	53	45	62	4.5
Low Poverty Index	36.2	36	9	55	11.1
Transportation Costs Index	9.7	9	6	16	2.1
Transit Trips Index	6.8	0	0	42	8.8

Source: HUD AFFH Dataset (AFFHT0006)

Table 5.62 Summary Statistics for Opportunity Indexes in the Austin-Round Rock MSA

	Mean	Median	Minimum	Maximum	Standard Deviation
Jobs Proximity Index	36.3	30.8	0.6	99	25.5
School Proficiency Index	64.5	69.5	1	99	26
Labor Market Engagement Index	73.7	77	3	99	19.1
Environmental Health Hazards Index	64.4	66	41	79	8.6
Low Poverty Index	68.7	75	2	99	25
Transportation Costs Index	59.6	56	34	94	13.9
Transit Trips Index	49.1	47	0	96	18.3

Source: HUD AFFH Dataset (AFFHT0006)

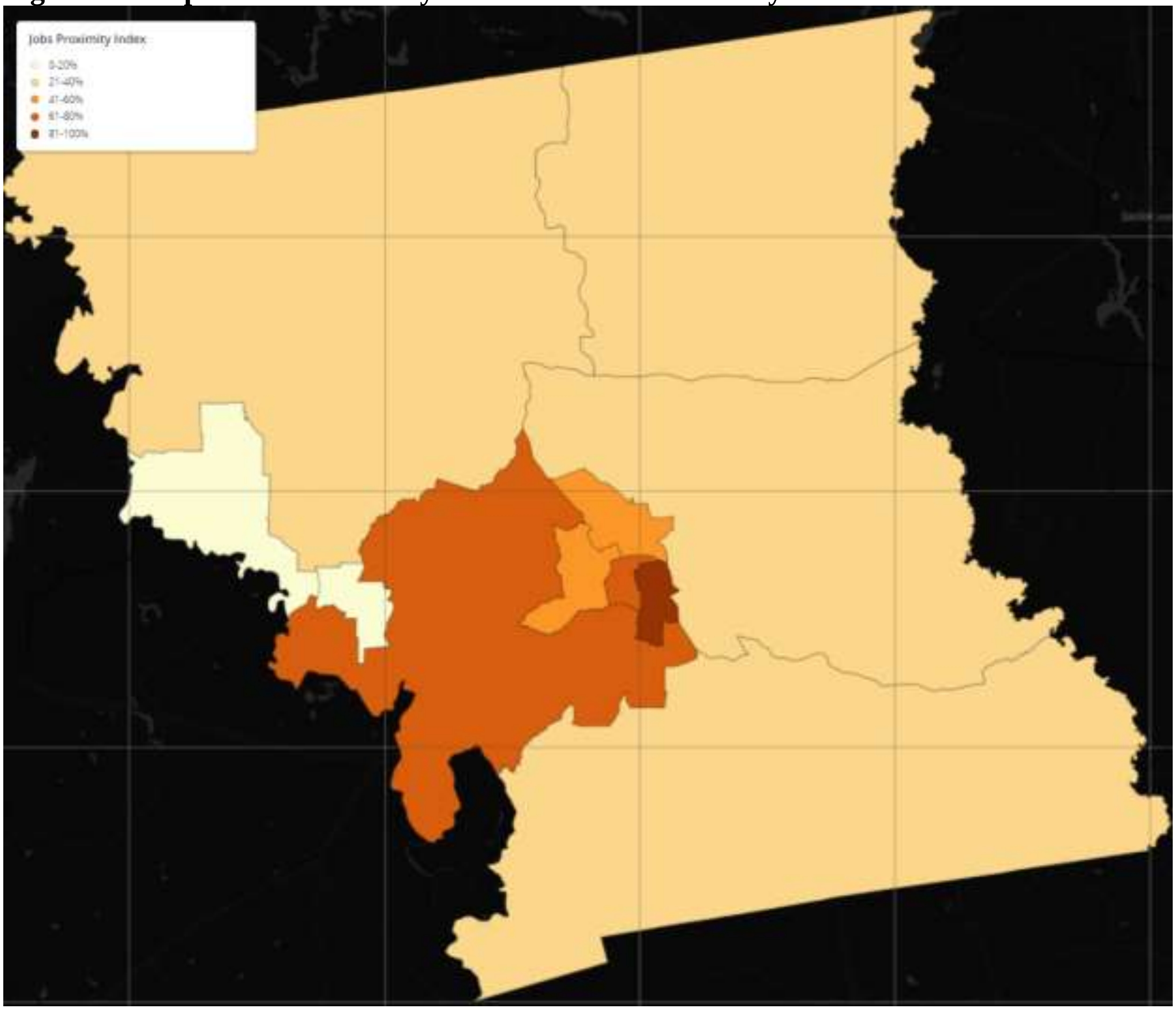
Table 5.63 Summary Statistics for Opportunity Indexes in McLennan County

	Mean	Median	Minimum	Maximum	Standard Deviation
Jobs Proximity Index	46.9	49.9	5	95.1	23.7
School Proficiency Index	60.3	75.1	1.2	97.8	30.9
Labor Market Engagement Index	64.6	73	3	91	22.1
Environmental Health Hazards Index	57.8	56	42	78	9.4
Low Poverty Index	59.4	71	2	91	25.4
Transportation Costs Index	14.9	11	5	51	8.8

Transit Trips Index	30.9	30	0	90	20.4

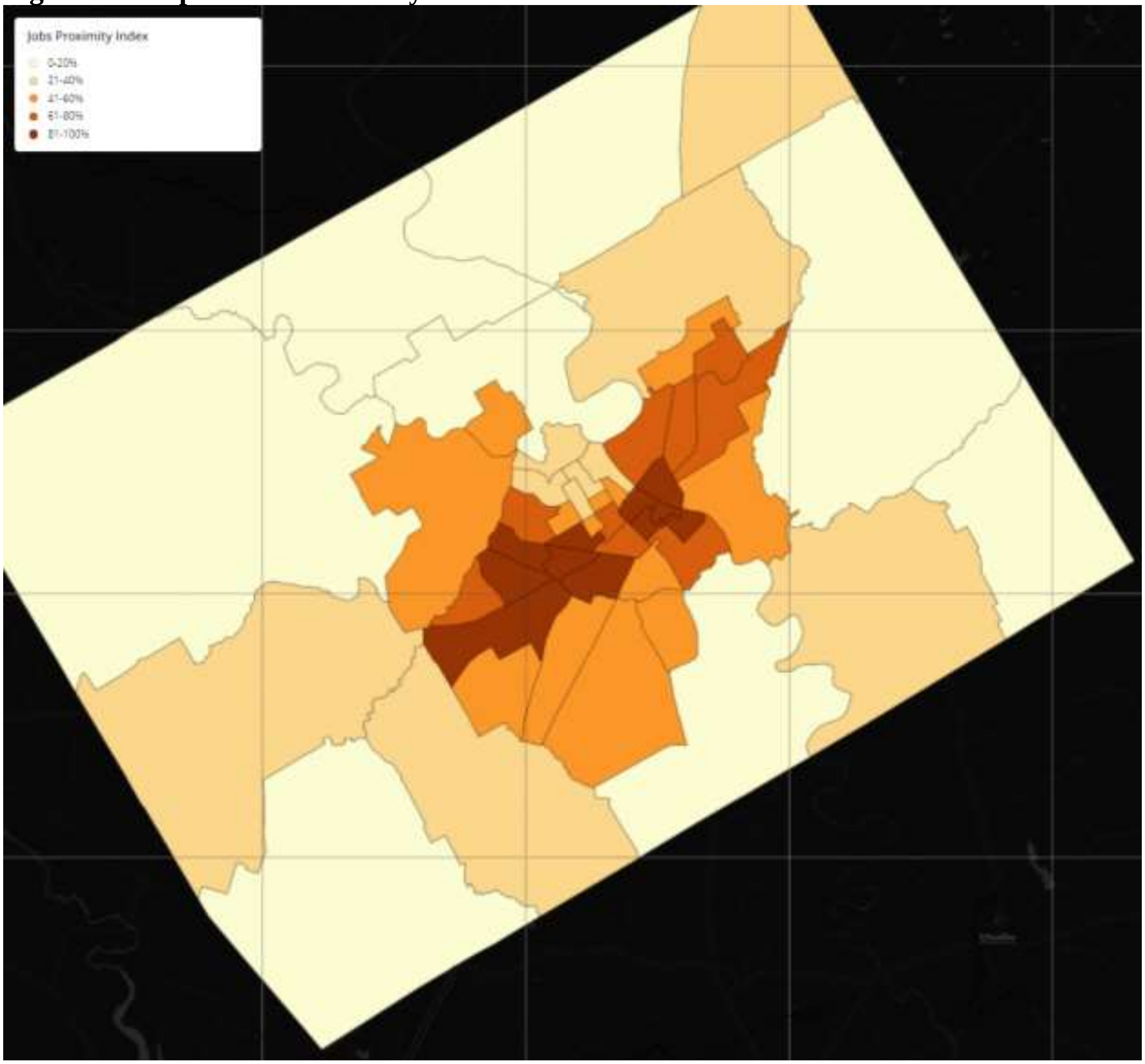
Source: HUD AFFH Dataset (AFFHT0006)

Figure 5.1 Map of Jobs Proximity Index in Anderson County



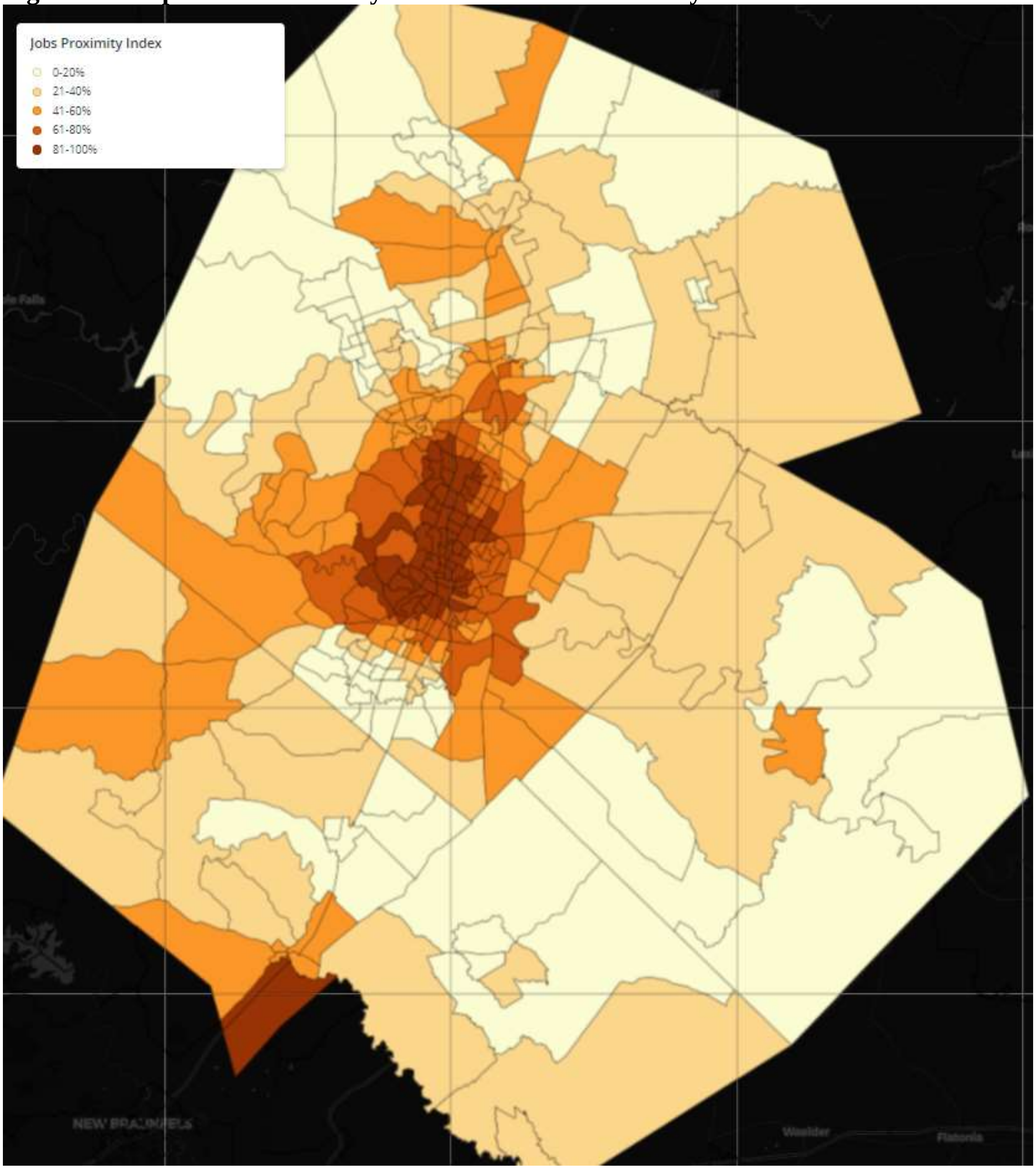
Source: HUD AFFH Dataset (AFFHT0006)

Figure 5.2 Map of Jobs Proximity Index in the Austin-Round Rock MSA



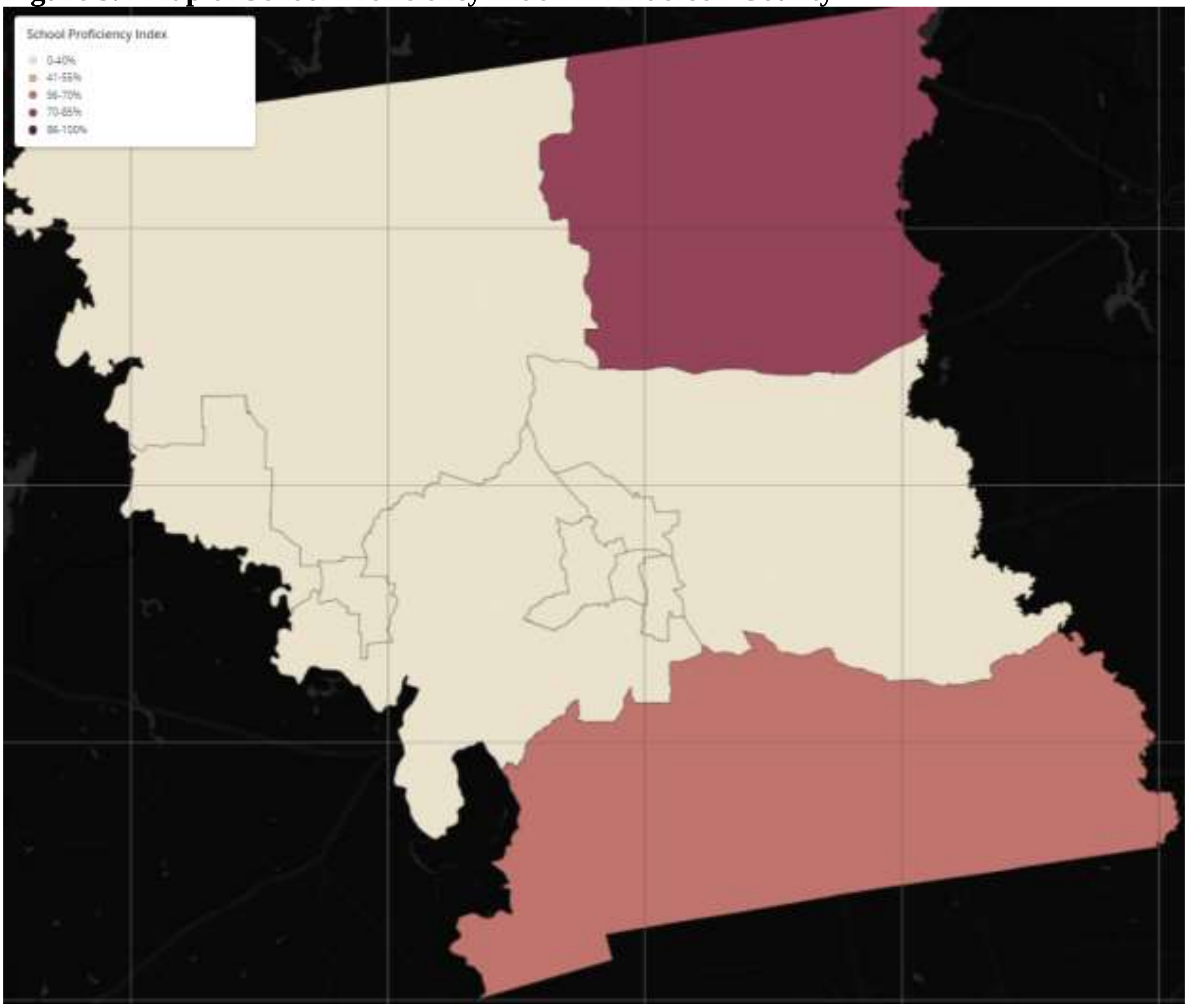
Source: HUD AFFH Dataset (AFFHT0006)

Figure 5.3 Map of Jobs Proximity Index in McLennan County



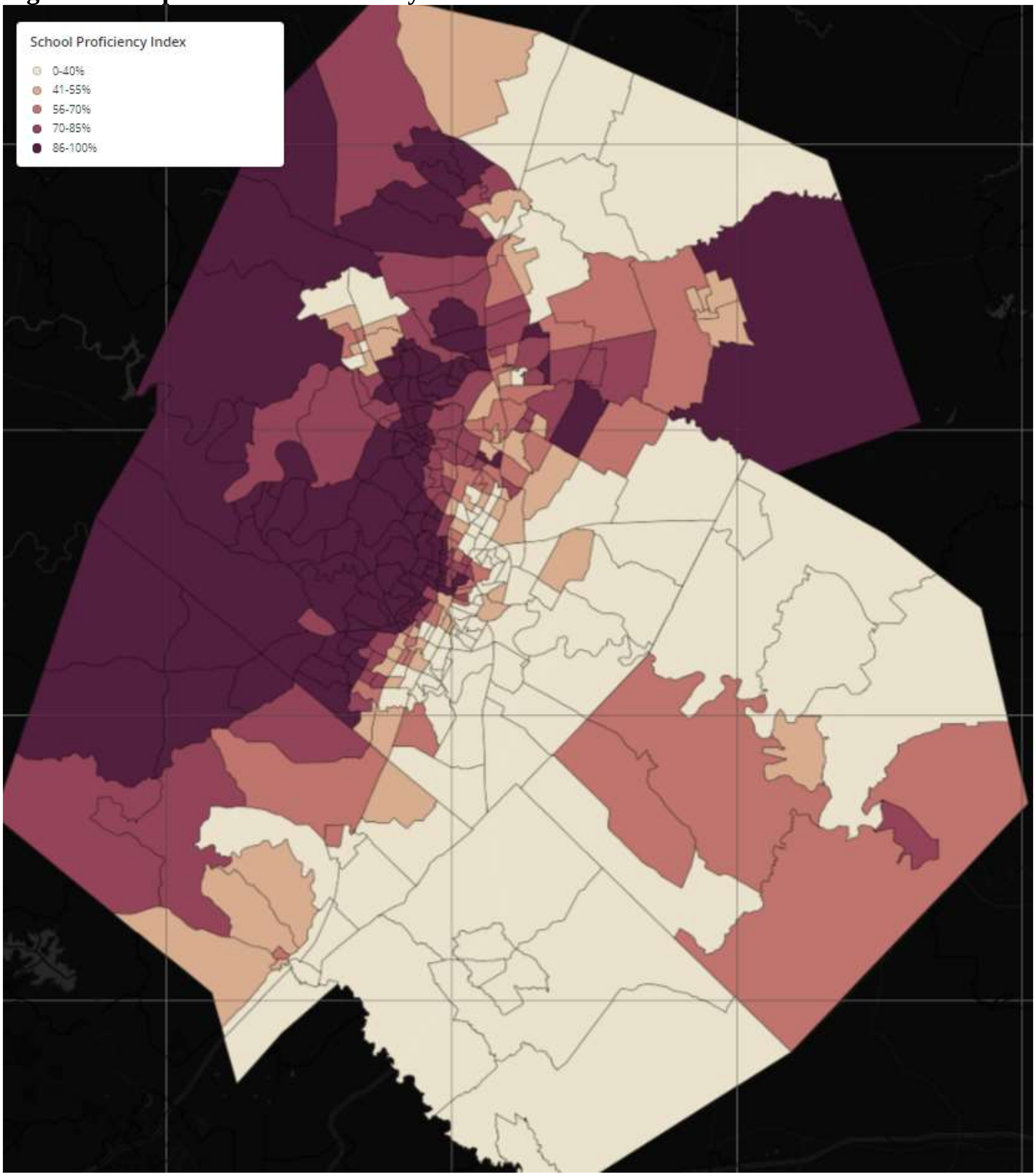
Source: HUD AFFH Dataset (AFFHT0006)

Figure 5.4 Map of School Proficiency Index in Anderson County



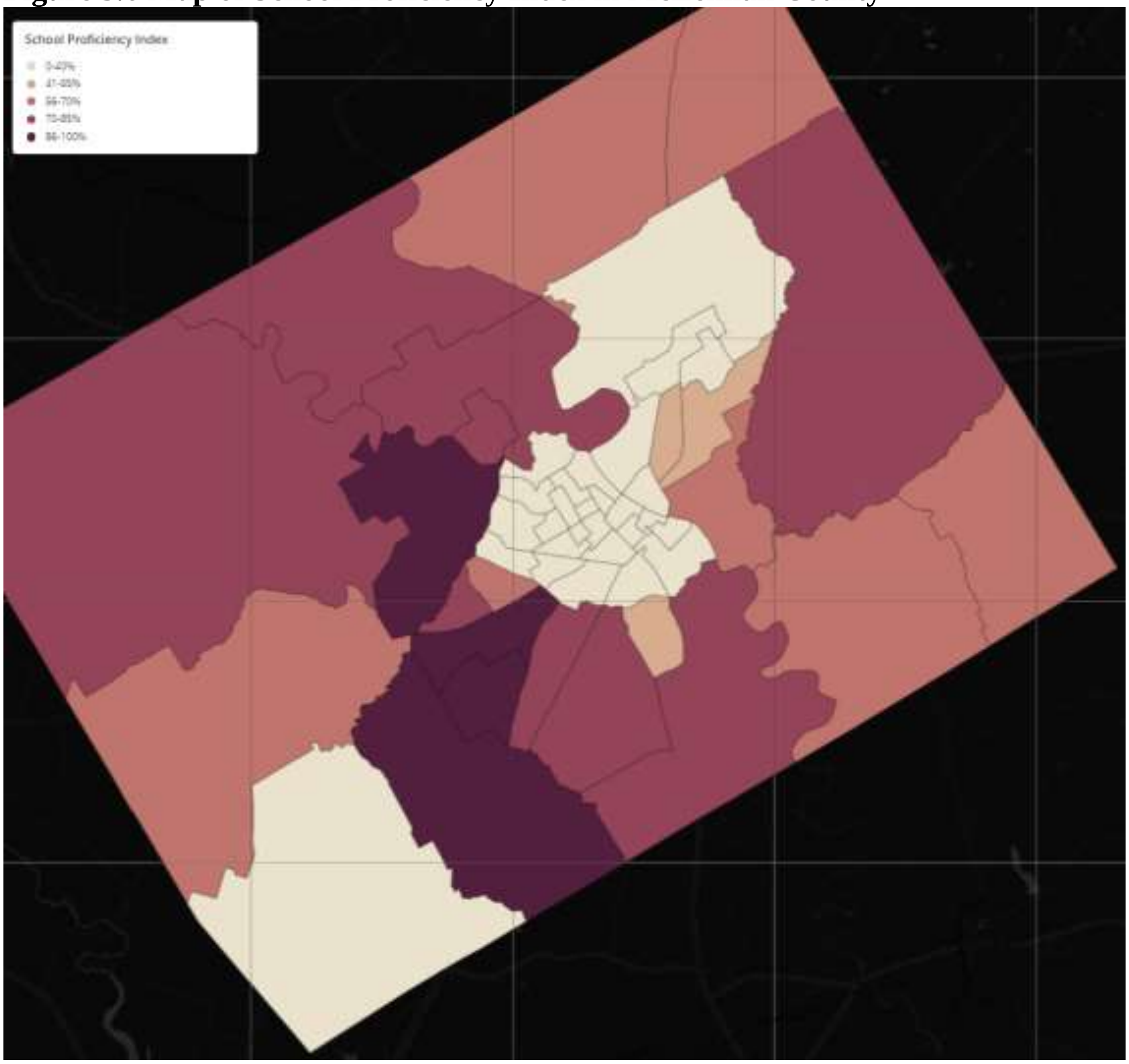
Source: HUD AFFH Dataset (AFFHT0006)

Figure 5.5 Map of School Proficiency Index in the Austin-Round Rock MSA



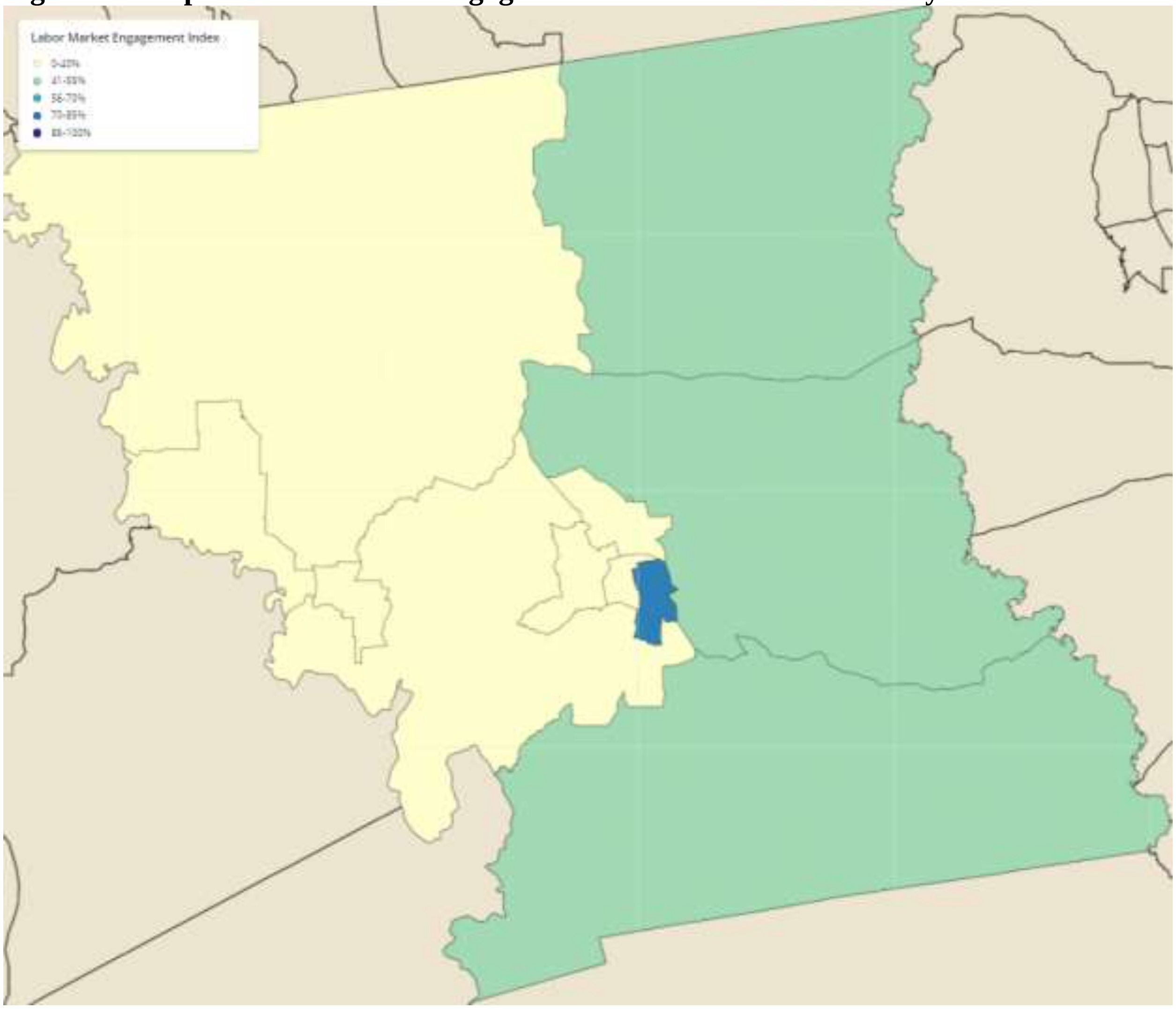
Source: HUD AFFH Dataset (AFFHT0006)

Figure 5.6 Map of School Proficiency Index in McLennan County



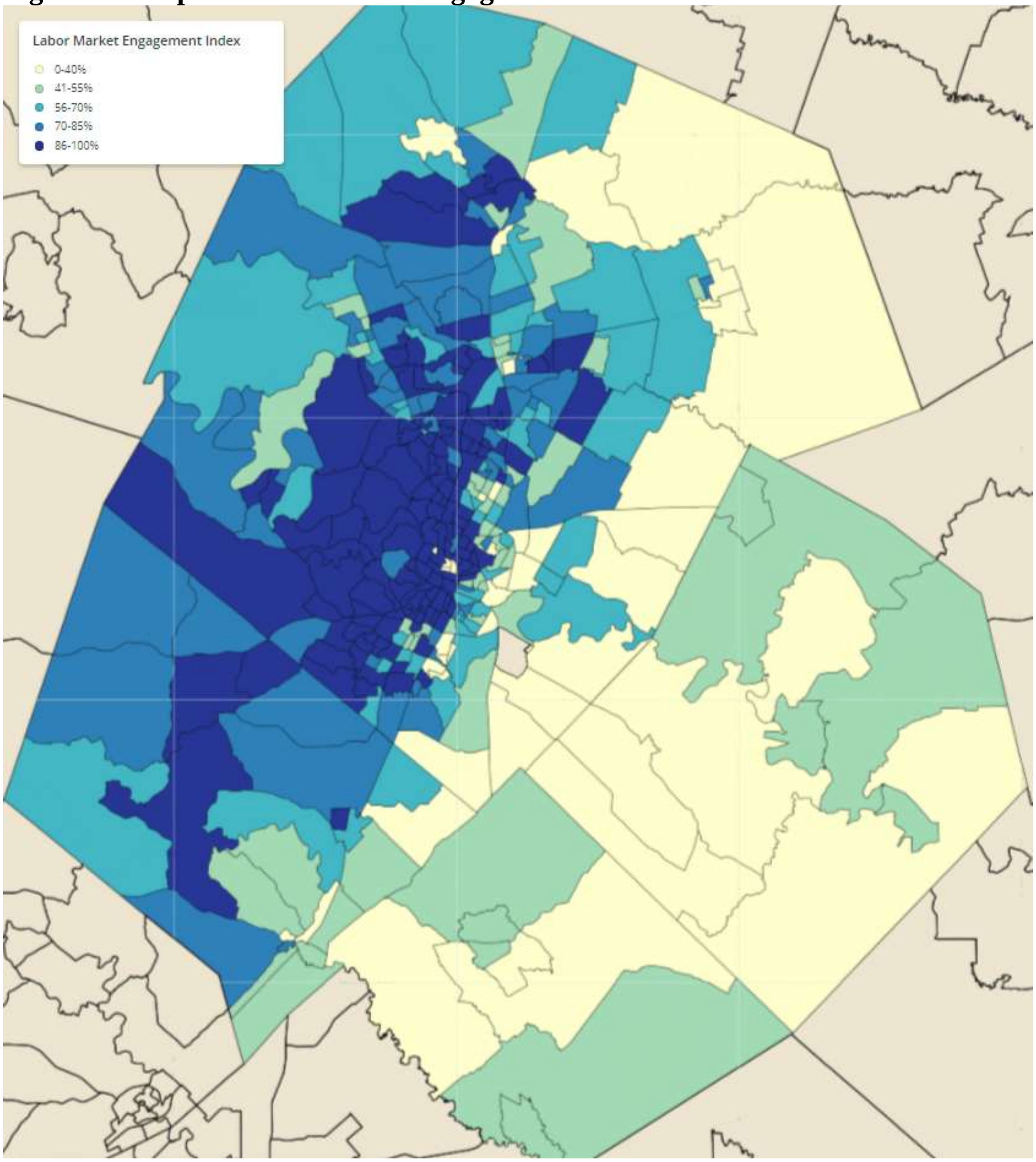
Source: HUD AFFH Dataset (AFFHT0006)

Figure 5.7 Map of Labor Market Engagement Index in Anderson County



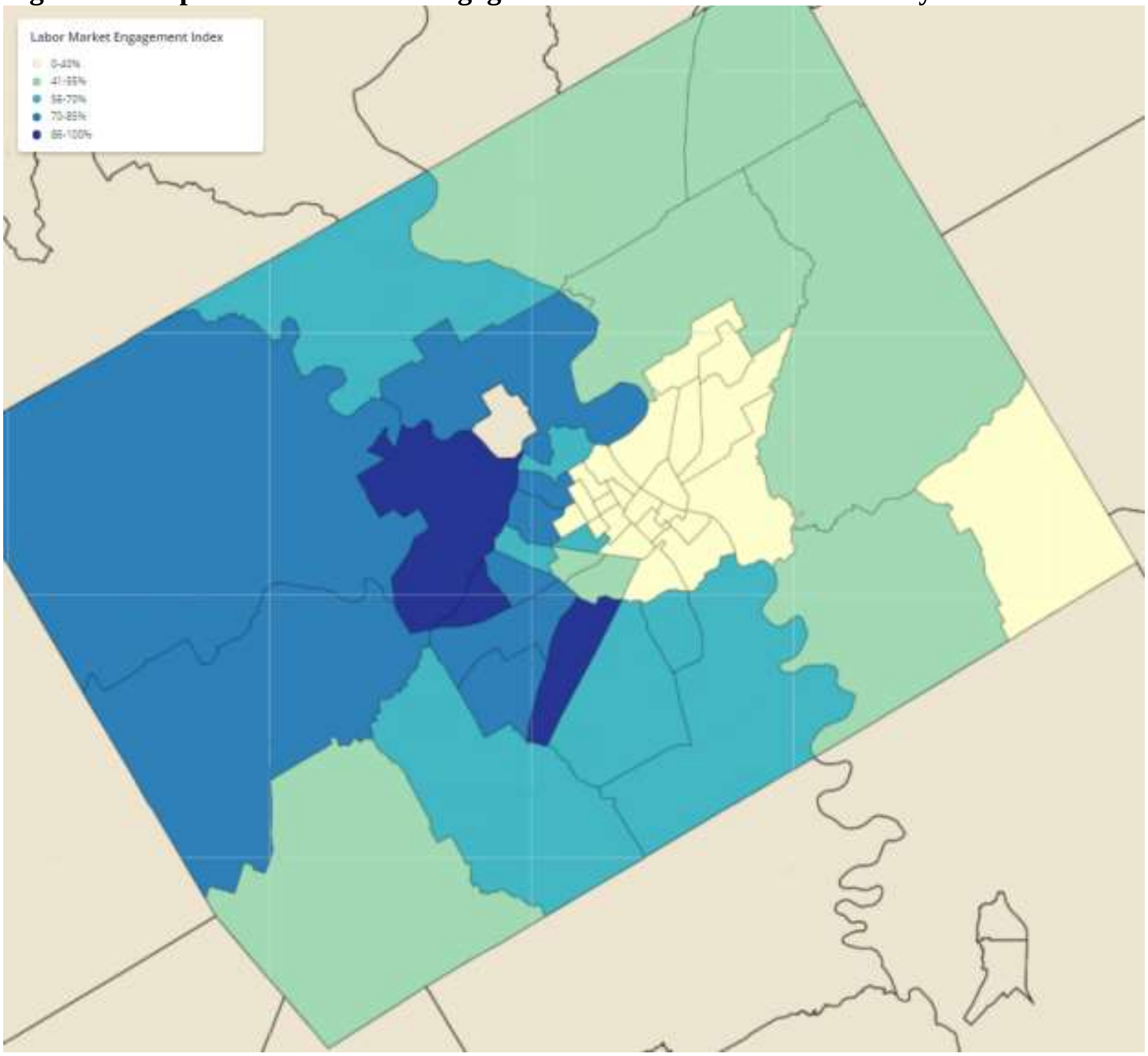
Source: HUD AFFH Dataset (AFFHT0006)

Figure 5.8 Map of Labor Market Engagement Index in the Austin-Round Rock MSA



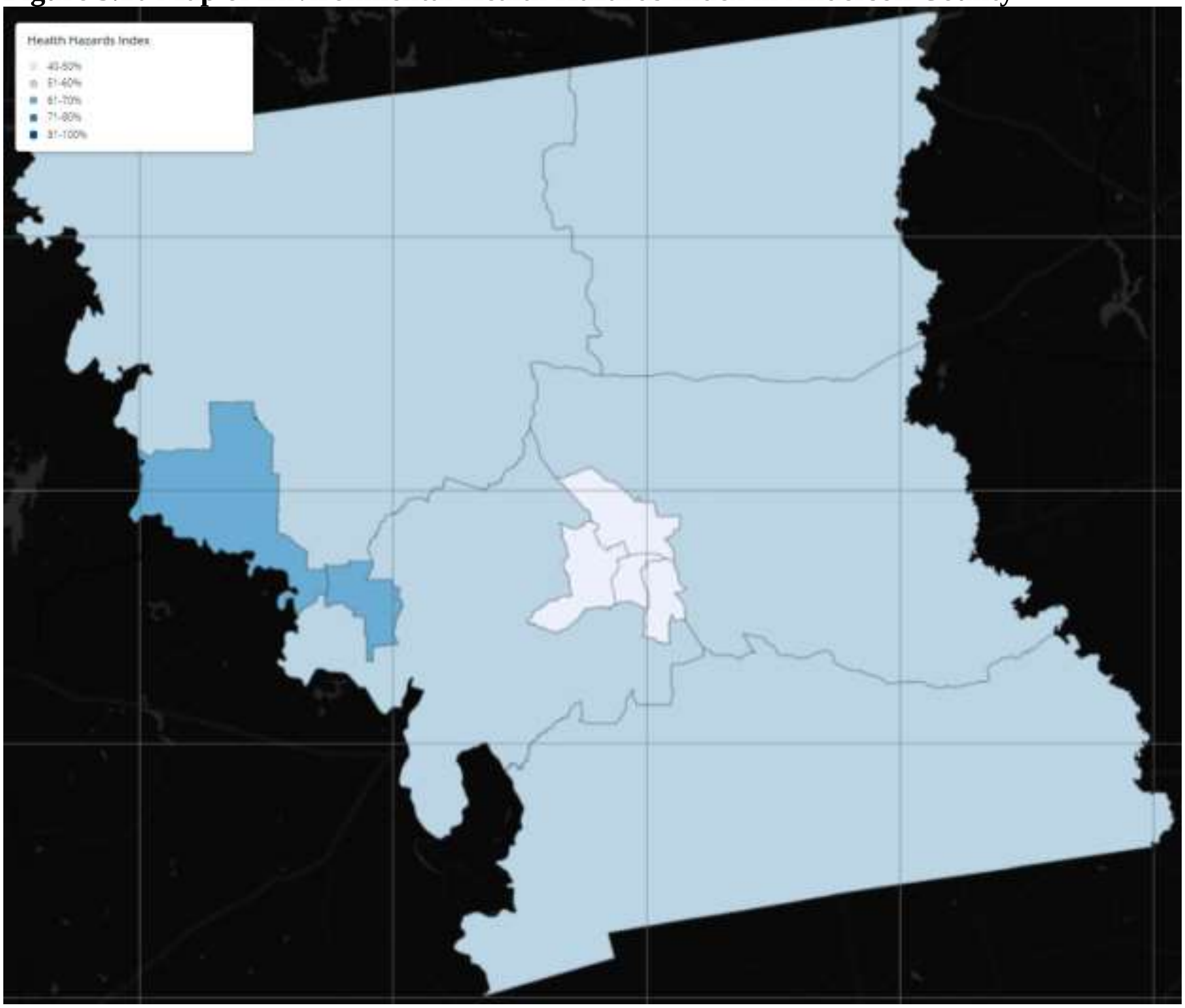
Source: HUD AFFH Dataset (AFFHT0006)

Figure 5.9 Map of Labor Market Engagement Index in McLennan County



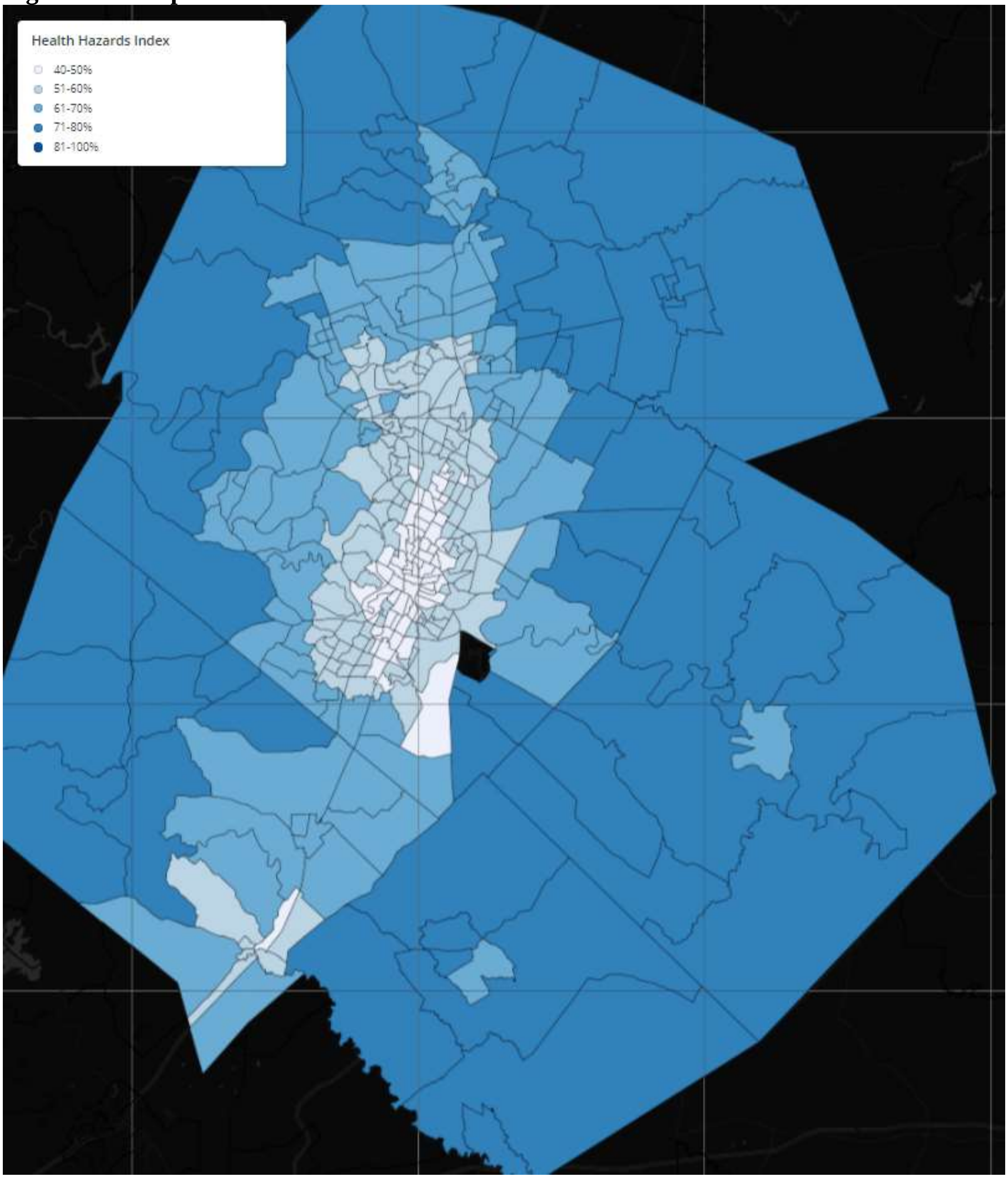
Source: HUD AFFH Dataset (AFFHT0006)

Figure 5.10 Map of Environmental Health Hazards Index in Anderson County



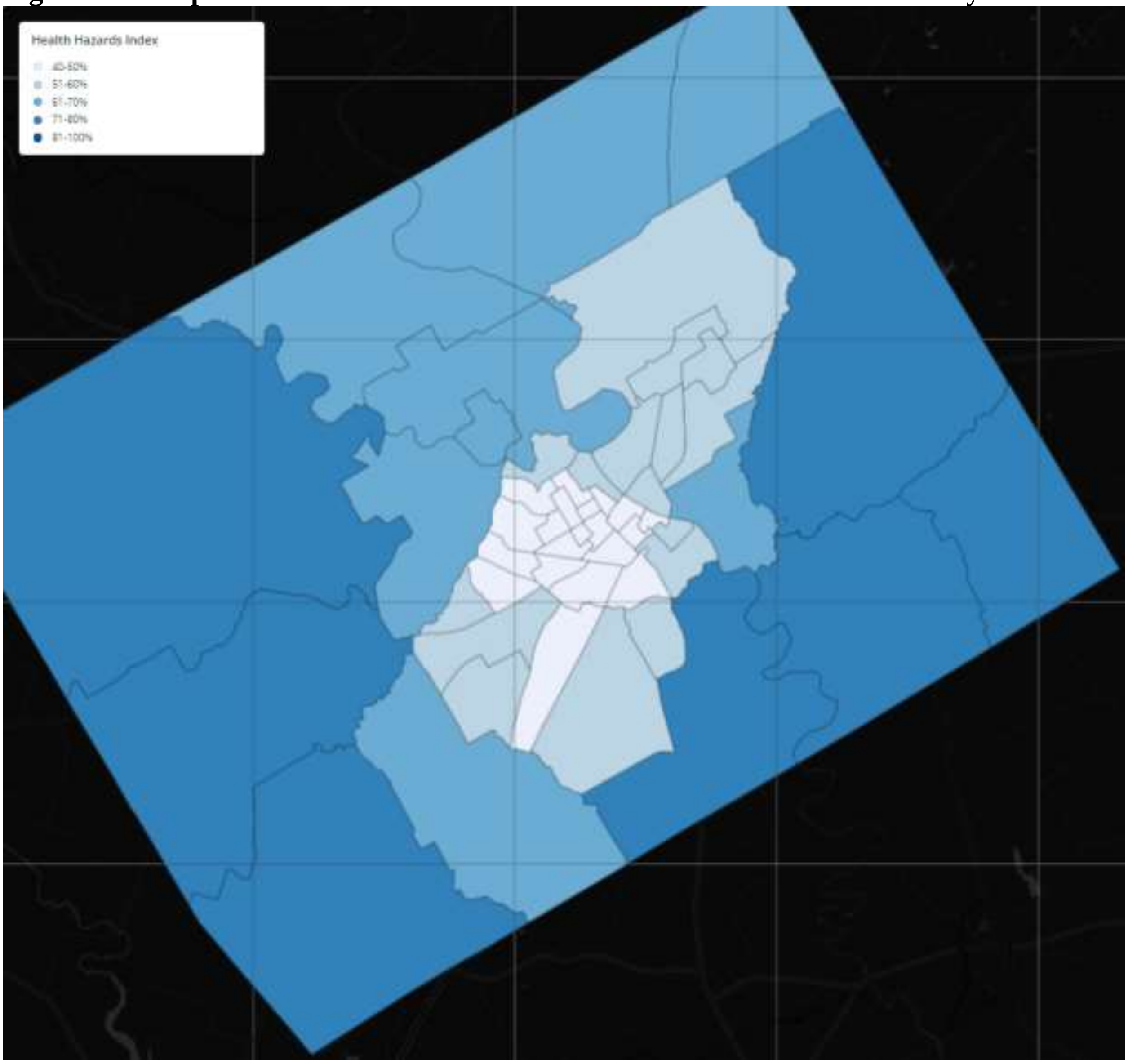
Source: HUD AFFH Dataset (AFFHT0006)

Figure 5.11 Map of Environmental Health Hazards Index in the Austin-Round Rock MSA



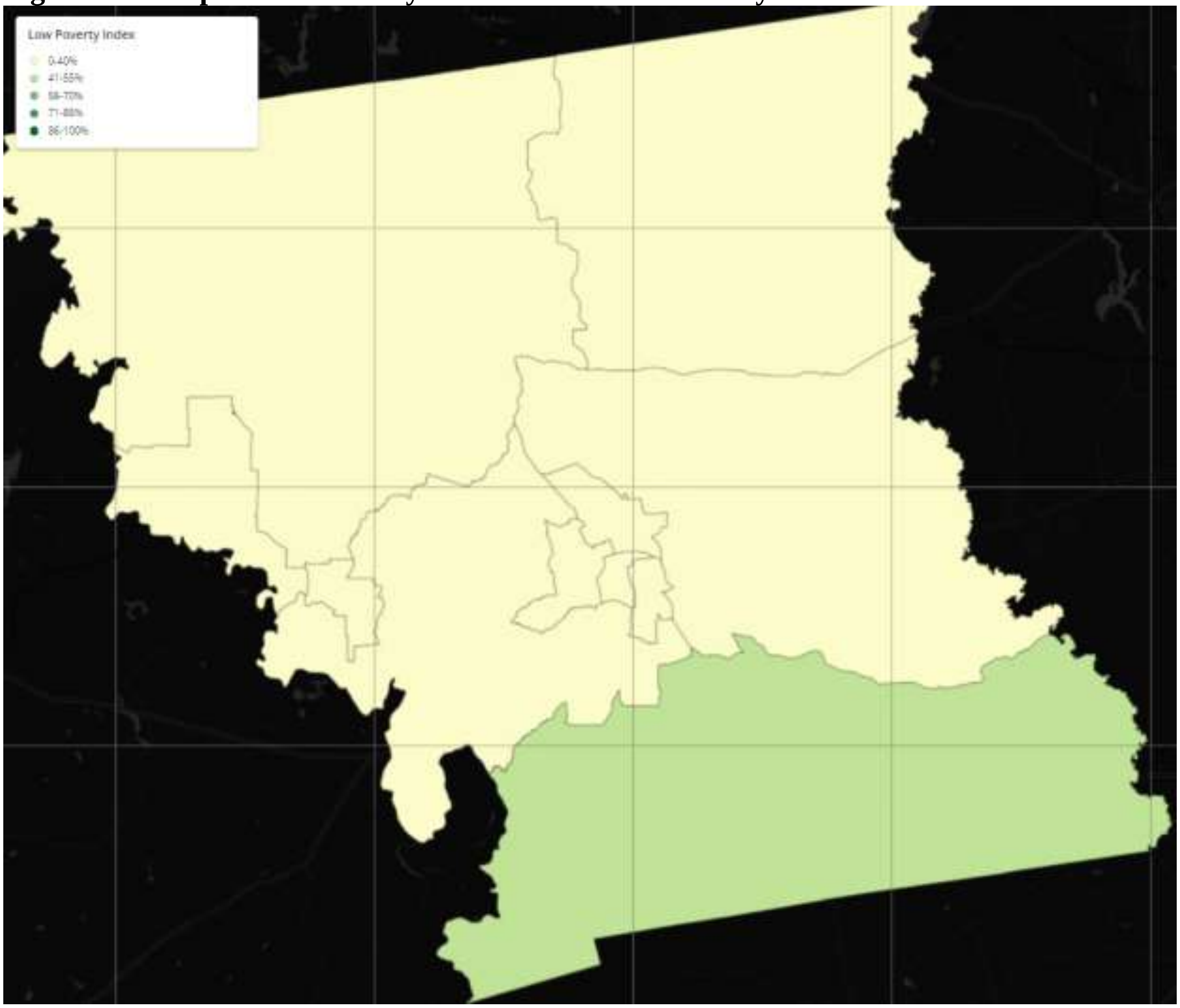
Source: HUD AFFH Dataset (AFFHT0006)

Figure 5.12 Map of Environmental Health Hazards Index in McLennan County



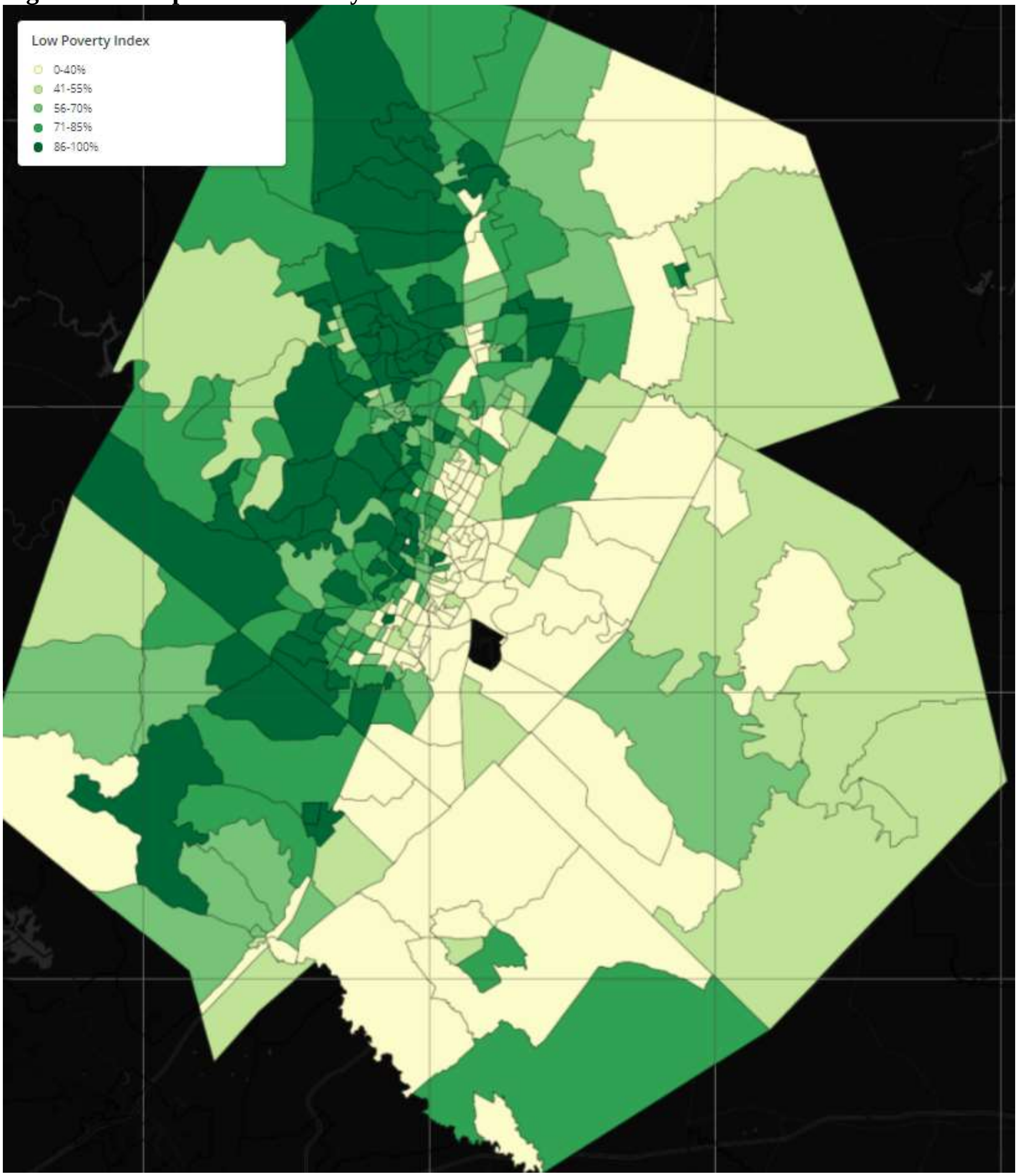
Source: HUD AFFH Dataset (AFFHT0006)

Figure 5.13 Map of Low Poverty Index in Anderson County



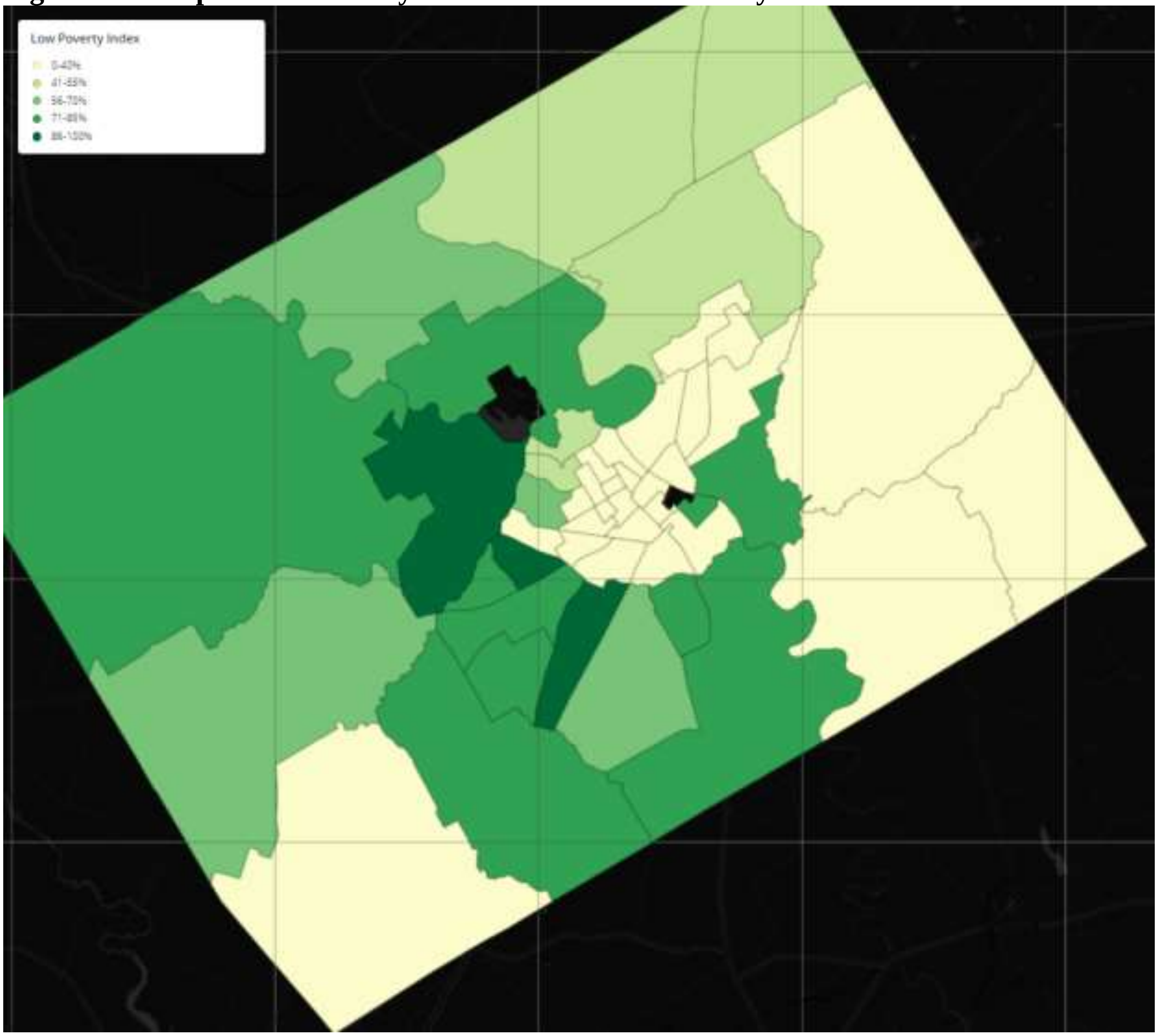
Source: HUD AFFH Dataset (AFFHT0006)

Figure 5.14 Map of Low Poverty Index in the Austin-Round Rock MSA



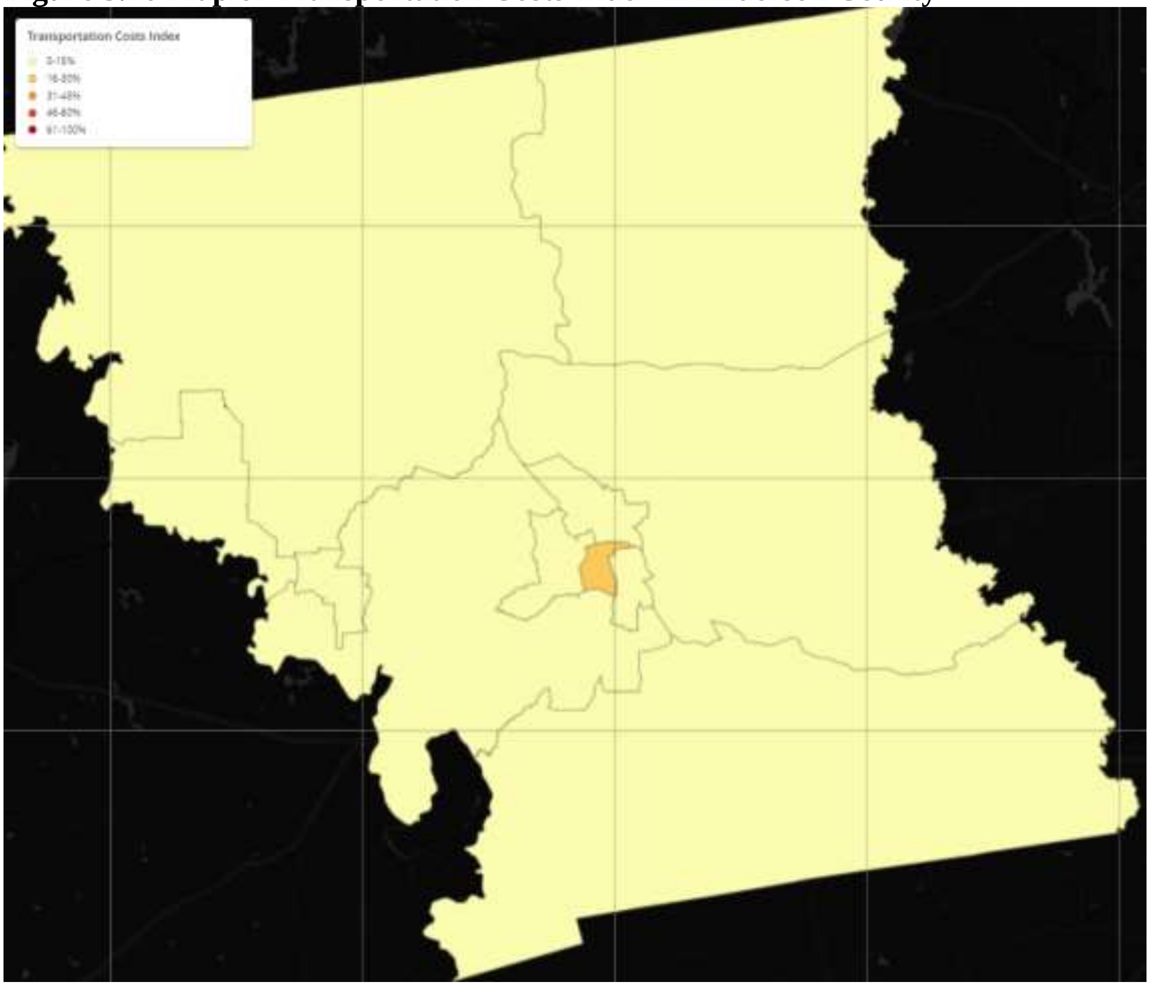
Source: HUD AFFH Dataset (AFFHT0006)

Figure 5.15 Map of Low Poverty Index in McLennan County



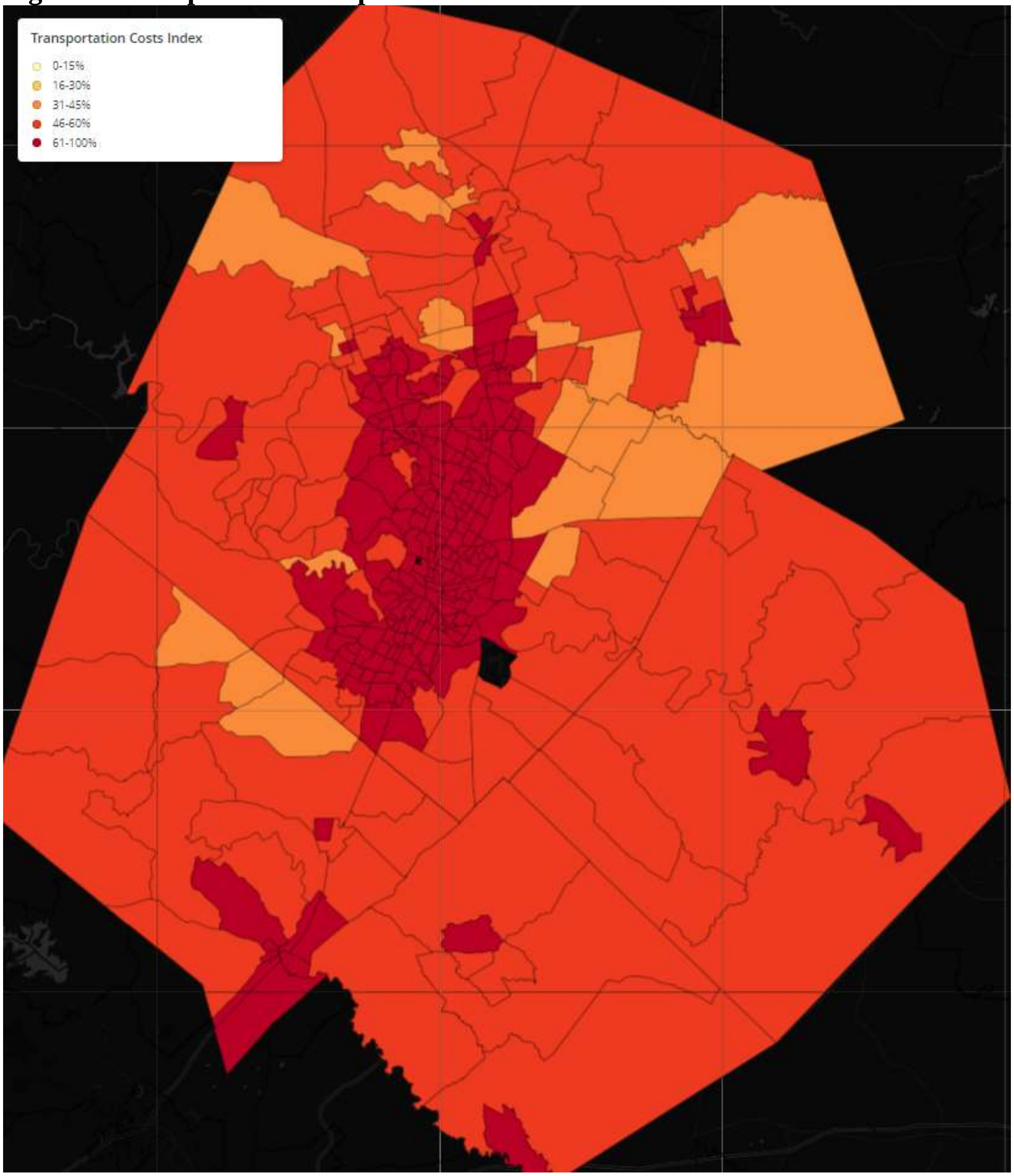
Source: HUD AFFH Dataset (AFFHT0006)

Figure 5.16 Map of Transportation Costs Index in Anderson County



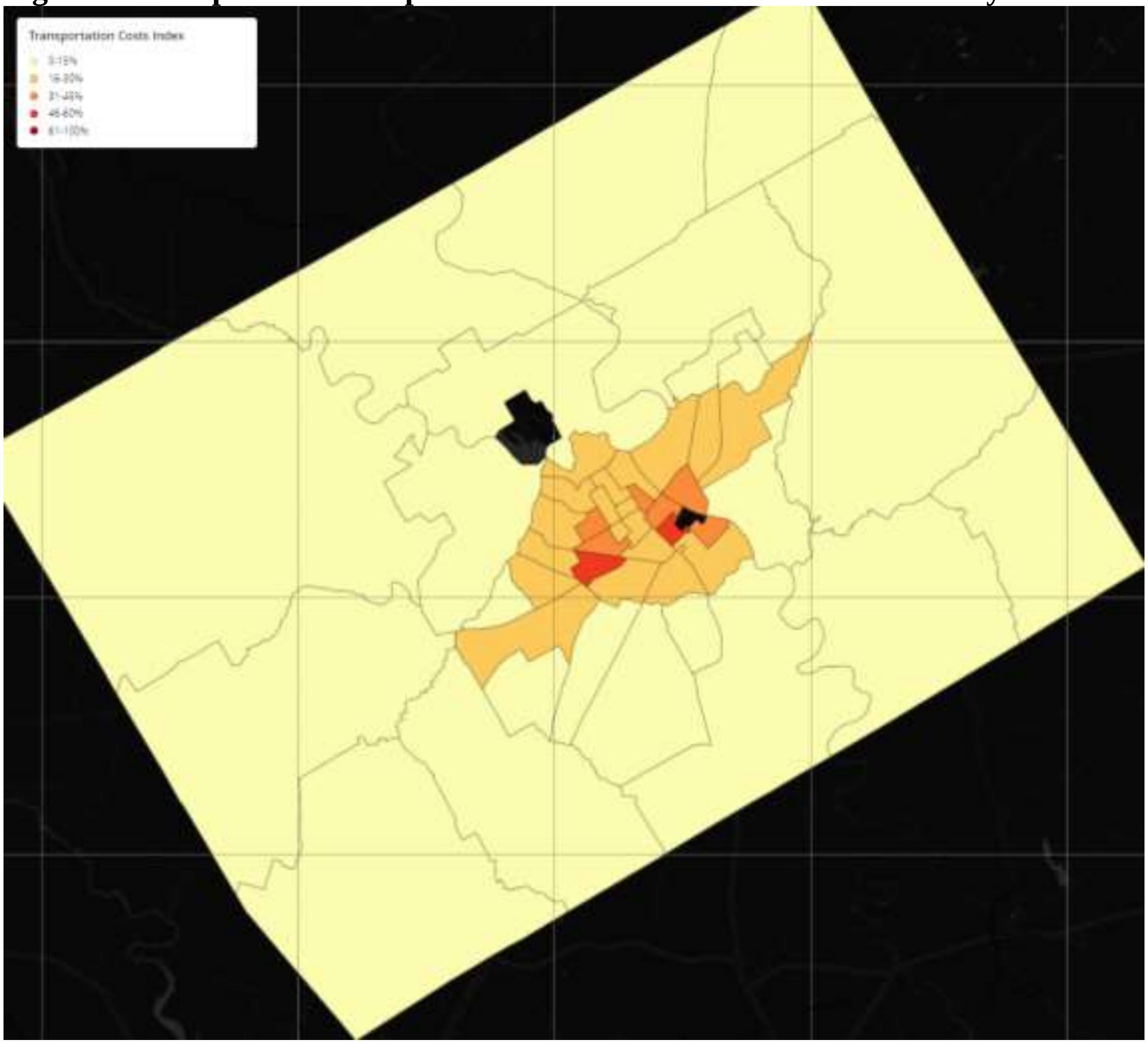
Source: HUD AFFH Dataset (AFFHT0006)

Figure 5.17 Map of the Transportation Costs Index in the Austin-Round Rock MSA



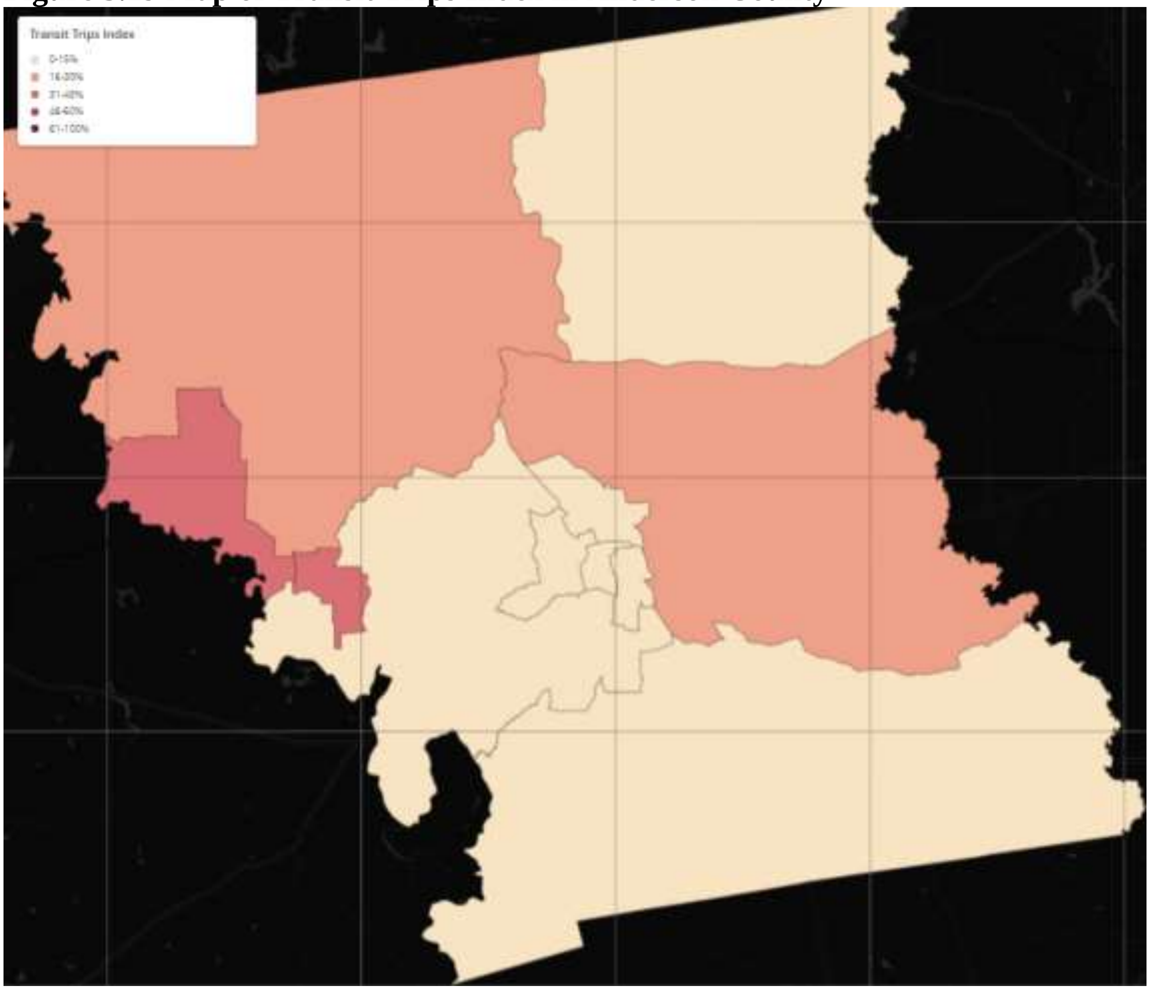
Source: HUD AFFH Dataset (AFFHT0006)

Figure 5.18 Map of the Transportation Costs Index in McLennan County



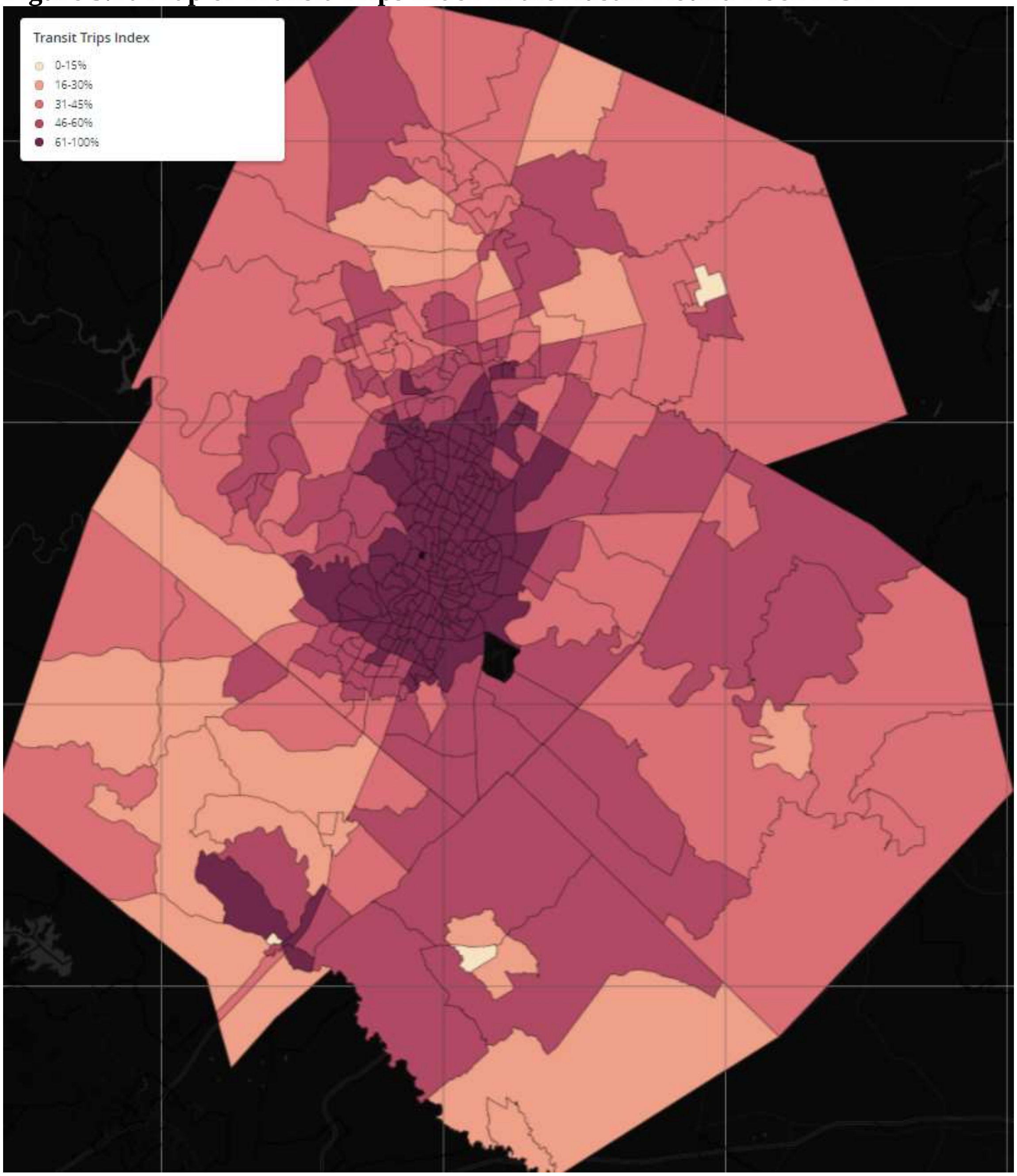
Source: HUD AFFH Dataset (AFFHT0006)

Figure 5.19 Map of Transit Trips Index in Anderson County



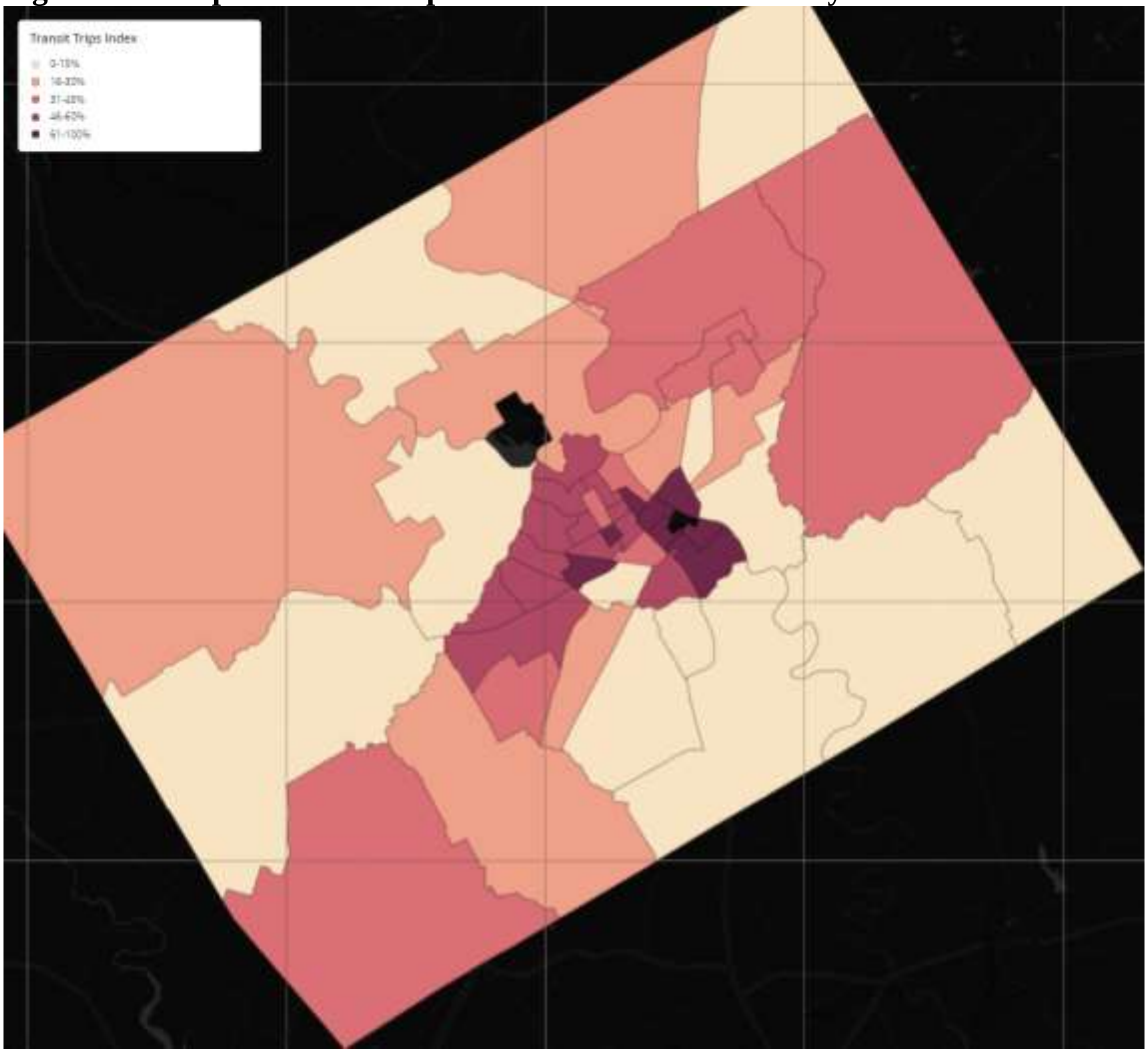
Source: HUD AFFH Dataset (AFFHT0006)

Figure 5.20 Map of Transit Trips Index in the Austin-Round Rock MSA



Source: HUD AFFH Dataset (AFFHT0006)

Figure 5.21 Map of Transit Trips Index in McLennan County



Source: HUD AFFH Dataset (AFFHT0006)

Opportunity Indexes by Loan Type

Conventional Loans

Table 5.64 Summary Statistics for Opportunity Indexes for Conventional Loans in Anderson County (2018)

	Mean	Median	Minimum	Maximum	Standard Deviation
Jobs Proximity Index	48.7	36.7	22.8	87.5	23.4

	Mean	Median	Minimum	Maximum	Standard Deviation
School Proficiency Index	38	22.3	18	84	25.5
Labor Market Engagement Index	47.1	51	8	75	18.5
Environmental Health Hazards Index	52.5	53	45	60	4.7
Low Poverty Index	36.5	36	9	55	12.3
Transportation Costs Index	9.6	9	6	16	2.3
Transit Trips Index	7.6	0	0	27	9.3

Source: HUD AFFH Dataset (AFFHT0006)

Table 5.65 Summary Statistics for Opportunity Indexes for Conventional Loans in Anderson County (2019)

	Mean	Median	Minimum	Maximum	Standard Deviation
Jobs Proximity Index	47.3	36.7	22.8	87.5	22.3
School Proficiency Index	38.6	22.3	18	84	25.7
Labor Market Engagement Index	47.3	47	8	75	17.2
Environmental Health Hazards Index	52.7	53	45	60	4.3
Low Poverty Index	36.6	36	9	55	12
Transportation Costs Index	9.4	9	6	16	2.1
Transit Trips Index	8	9	0	27	9

Source: HUD AFFH Dataset (AFFHT0006)

Table 5.66 Summary Statistics for Opportunity Indexes for Conventional Loans in the Austin-Round Rock MSA (2018)

	Mean	Median	Minimum	Maximum	Standard Deviation
Jobs Proximity Index	40.1	36.5	0.6	99	26.3
School Proficiency Index	68	74.3	1	99	25.3
Labor Market Engagement Index	76.3	82	3	99	18.8
Environmental Health Hazards Index	62.8	64	41	79	8.7
Low Poverty Index	69.4	77	2	99	25.6
Transportation Costs Index	61.9	59	34	94	14.3
Transit Trips Index	51.8	49	0	96	18.8

Source: HUD AFFH Dataset (AFFHT0006)

Table 5.67 Summary Statistics for Opportunity Indexes for Conventional Loans in the Austin-Round Rock MSA (2019)

	Mean	Median	Minimum	Maximum	Standard Deviation
Jobs Proximity Index	39.2	33	0.6	99	26.6
School Proficiency Index	67.3	73.4	1	99	25.2
Labor Market Engagement Index	75.9	81	3	99	18.9
Environmental Health Hazards Index	63.2	65	41	79	8.8

	Mean	Median	Minimum	Maximum	Standard Deviation
Low Poverty Index	69.8	77	2	99	25.2
Transportation Costs Index	61.2	58	34	94	14.6
Transit Trips Index	51.4	49	0	96	18.9

Source: HUD AFFH Dataset (AFFHT0006)

Table 5.68 Summary Statistics for Opportunity Indexes for Conventional Loans in McLennan County (2018)

	Mean	Median	Minimum	Maximum	Standard Deviation
Jobs Proximity Index	48	49.9	5	95.1	25.1
School Proficiency Index	59.9	75.1	1.2	97.8	31.9
Labor Market Engagement Index	65.5	73	3	91	22
Environmental Health Hazards Index	57.5	55	42	78	9.9
Low Poverty Index	60	73	2	91	26
Transportation Costs Index	15.8	11.5	5	51	9.9
Transit Trips Index	32.3	30	0	90	21.2

Source: HUD AFFH Dataset (AFFHT0006)

Table 5.69 Summary Statistics for Opportunity Indexes for Conventional Loans in McLennan County (2019)

	Mean	Median	Minimum	Maximum	Standard Deviation
Jobs Proximity Index	48.1	49.9	5	95.1	23.7

	Mean	Median	Minimum	Maximum	Standard Deviation
School Proficiency Index	61.2	75.1	1.2	97.8	30.9
Labor Market Engagement Index	66.5	73	3	91	20.9
Environmental Health Hazards Index	57.5	55	42	78	9.3
Low Poverty Index	61	73	2	91	24.2
Transportation Costs Index	15.2	12	5	51	8.8
Transit Trips Index	32.1	30	0	90	21

Source: HUD AFFH Dataset (AFFHT0006)

FHA-Insured Loans

Table 5.70 Summary Statistics for Opportunity Indexes for FHA-Insured Loans in Anderson County (2018)

	Mean	Median	Minimum	Maximum	Standard Deviation
Jobs Proximity Index	60.3	55.9	23.6	87.5	20.4
School Proficiency Index	31	22.3	18	84	20.9
Labor Market Engagement Index	45	40	8	75	22.1
Environmental Health Hazards Index	50.3	48	45	58	4.3
Low Poverty Index	34.9	36	9	55	10.8
Transportation Costs Index	10.2	11	6	16	2.1

Transit Trips Index	4.1	0	0	20	6.1

Source: HUD AFFH Dataset (AFFHT0006)

Table 5.71 Summary Statistics for Opportunity Indices for FHA-Isnured Loans in Anderson County (2019)

	Mean	Median	Minimum	Maximum	Standard Deviation
Jobs Proximity Index	57	55.9	2	87.5	23.9
School Proficiency Index	32.8	22.3	18	84	22.6
Labor Market Engagement Index	47.8	49	0	75	21.6
Environmental Health Hazards Index	51.1	48.5	45	62	4.6
Low Poverty Index	36.1	36	9	55	9.7
Transportation Costs Index	10	9	6	16	2.1
Transit Trips Index	5.6	0	0	42	8.7

Source: HUD AFFH Dataset (AFFHT0006)

Table 5.72 Summary Statistics for Opportunity Indices for FHA-Insured Loans in the Austin-Round Rock MSA (2018)

	Mean	Median	Minimum	Maximum	Standard Deviation
Jobs Proximity Index	26.9	24.2	0.6	95	20.1
School Proficiency Index	51.5	51	1	98.3	25.6
Labor Market Engagement Index	64.9	66	3	98	17.7

	Mean	Median	Minimum	Maximum	Standard Deviation
Environmental Health Hazards Index	67.7	69	45	79	6.4
Low Poverty Index	63.1	70	2	99	24.7
Transportation Costs Index	55.3	53	34	94	10.5
Transit Trips Index	42.8	42	0	94	14.2

Source: HUD AFFH Dataset (AFFHT0006)

Table 5.73 Summary Statistics for Opportunity Indices for FHA-Insured Loans in the Austin-Round Rock MSA (2019)

	Mean	Median	Minimum	Maximum	Standard Deviation
Jobs Proximity Index	25.6	24.2	0.6	92.8	18.8
School Proficiency Index	51.9	51	1	98.6	25.3
Labor Market Engagement Index	64.9	66	3	99	17.3
Environmental Health Hazards Index	68.4	70	41	79	6.1
Low Poverty Index	63.8	70	2	99	23.7
Transportation Costs Index	54	51	34	90	9.8
Transit Trips Index	41.4	40	0	91	13.9

Source: HUD AFFH Dataset (AFFHT0006)

Table 5.74 Summary Statistics for Opportunity Indices for FHA-Insured Loans in McLennan County (2018)

	Mean	Median	Minimum	Maximum	Standard Deviation
Jobs Proximity Index	47.8	50	5	95.1	22.9
School Proficiency Index	52.4	59.9	1.2	97.8	32.2
Labor Market Engagement Index	57.8	68	3	91	24.7
Environmental Health Hazards Index	56.6	56	42	78	9.2
Low Poverty Index	52.8	59	2	91	27.7
Transportation Costs Index	15.6	12	5	51	8.5
Transit Trips Index	30.3	30	0	82	19.8

Source: HUD AFFH Dataset (AFFHT0006)

Table 5.75 Summary Statistics for Opportunity Indices for FHA-Insured Loans in McLennan County (2019)

	Mean	Median	Minimum	Maximum	Standard Deviation
Jobs Proximity Index	46.5	49.9	5	95.1	23.4
School Proficiency Index	57.6	73	1.2	97.8	31.4
Labor Market Engagement Index	61.2	70	3	91	23.8
Environmental Health Hazards Index	57.3	56	42	78	9.4
Low Poverty Index	55.9	71	2	91	27

Transportation Costs Index	15.2	12	5	51	8.5
Transit Trips Index	30.6	30	0	90	19.1

Source: HUD AFFH Dataset (AFFHT0006)

VA-Guaranteed Loans

Table 5.76 Summary Statistics for Opportunity Indices for VA-Guaranteed Loans in Anderson County (2018)

	Mean	Median	Minimum	Maximum	Standard Deviation
Jobs Proximity Index	57.7	64.7	23.6	87.5	23.9
School Proficiency Index	36.8	27	18	84	25.3
Labor Market Engagement Index	45.7	51	13	75	23.9
Environmental Health Hazards Index	51.8	54	46	58	4.1
Low Poverty Index	38.3	36	31	55	7.1
Transportation Costs Index	9.8	11	6	12	2.1
Transit Trips Index	6	0	0	20	7.1

Source: HUD AFFH Dataset (AFFHT0006)

Table 5.77 Summary Statistics for Opportunity Indices for VA-Guaranteed Loans in Anderson County (2019)

	Mean	Median	Minimum	Maximum	Standard Deviation
Jobs Proximity Index	48.4	51.9	22.8	87.5	22.2

	Mean	Median	Minimum	Maximum	Standard Deviation
School Proficiency Index	37.4	27	18	84	24.9
Labor Market Engagement Index	40.3	40	13	75	19.9
Environmental Health Hazards Index	53.1	54	46	60	4.4
Low Poverty Index	35.6	36	9	55	10.6
Transportation Costs Index	9.5	9	6	12	2.1
Transit Trips Index	8.6	9	0	27	9.7

Source: HUD AFFH Dataset (AFFHT0006)

Table 5.78 Summary Statistics for Opportunity Indices for VA-Guaranteed Loans in the Austin-Round Rock MSA (2018)

	Mean	Median	Minimum	Maximum	Standard Deviation
Jobs Proximity Index	28.1	24.5	0.6	99	20.2
School Proficiency Index	62.6	68.8	1	98.7	25.3
Labor Market Engagement Index	70.2	73	3	99	17.4
Environmental Health Hazards Index	67.9	70	41	79	6.6
Low Poverty Index	70.3	75	2	99	22.9
Transportation Costs Index	54.8	52	34	94	11.1
Transit Trips Index	42.5	41	0	94	14.8

Source: HUD AFFH Dataset (AFFHT0006)

Table 5.79 Summary Statistics for Opportunity Indices for VA-Guaranteed Loans in the Austin-Round Rock MSA (2019)

	Mean	Median	Minimum	Maximum	Standard Deviation
Jobs Proximity Index	26.8	24.2	0.6	99	19.4
School Proficiency Index	61.3	62.2	2.5	98.6	25.2
Labor Market Engagement Index	69.3	73	3	99	17.5
Environmental Health Hazards Index	68.6	70	43	79	6.1
Low Poverty Index	70.8	75	2	99	22.4
Transportation Costs Index	53.7	51	34	94	10
Transit Trips Index	40.7	40	0	92	14.1

Source: HUD AFFH Dataset (AFFHT0006)

Table 5.80 Summary Statistics for Opportunity Indices for VA-Guaranteed Loans in McLennan County (2018)

	Mean	Median	Minimum	Maximum	Standard Deviation
Jobs Proximity Index	41.2	38.9	5	95.1	22.3
School Proficiency Index	64.4	79	1.2	97.8	29.3
Labor Market Engagement Index	66.2	73	5	91	21
Environmental Health Hazards Index	59.9	60.5	42	78	9.2
Low Poverty Index	61.8	73	6	91	24.1

Transportation Costs Index	13.1	9	5	49	7.7
Transit Trips Index	28.2	26	0	90	20.1

Source: HUD AFFH Dataset (AFFHT0006)

Table 5.81 Summary Statistics for Opportunity Indices for VA-Guaranteed Loans in McLennan County (2019)

	Mean	Median	Minimum	Maximum	Standard Deviation
Jobs Proximity Index	43.6	48.7	5	95.1	22.6
School Proficiency Index	67.9	79	1.2	97.8	26.6
Labor Market Engagement Index	67.4	73	3	91	20.1
Environmental Health Hazards Index	59.4	58	42	78	8.9
Low Poverty Index	63	73	6	91	23.2
Transportation Costs Index	12.7	9	5	51	7.1
Transit Trips Index	27.3	26	0	76	18.6

Source: HUD AFFH Dataset (AFFHT0006)

RHS-Guaranteed Loans

Table 5.82 Summary Statistics for Opportunity Indices for RHS-Guaranteed Loans in Anderson County (2018)

	Mean	Median	Minimum	Maximum	Standard Deviation
Jobs Proximity Index	58.7	55.9	22.8	87.5	21

	Mean	Median	Minimum	Maximum	Standard Deviation
School Proficiency Index	27.5	22.3	18	69	17.1
Labor Market Engagement Index	48.8	40	13	75	18.2
Environmental Health Hazards Index	49.8	48	46	60	4.7
Low Poverty Index	34.5	35	9	55	11.4
Transportation Costs Index	10	9	8	12	1.6
Transit Trips Index	4	0	0	27	7.5

Source: HUD AFFH Dataset (AFFHT0006)

Table 5.83 Summary Statistics for Opportunity Indices for RHS-Guaranteed Loans in Anderson County (2019)

	Mean	Median	Minimum	Maximum	Standard Deviation
Jobs Proximity Index	55.8	55.9	23.6	87.5	20.6
School Proficiency Index	36	22.3	18	84	25.3
Labor Market Engagement Index	43.7	38	13	75	19.6
Environmental Health Hazards Index	49.9	48	46	58	4.1
Low Poverty Index	35.4	36	31	55	5.7
Transportation Costs Index	9.3	9	6	12	2
Transit Trips Index	2.8	0	0	13	5.2

Source: HUD AFFH Dataset (AFFHT0006)

Table 5.84 Summary Statistics for Opportunity Indices for RHS-Guaranteed Loans in the Austin-Round Rock MSA (2018)

	Mean	Median	Minimum	Maximum	Standard Deviation
Jobs Proximity Index	22.7	21	0.6	59.9	15.2
School Proficiency Index	42.5	32	1	92.7	25.2
Labor Market Engagement Index	56.5	60	3	92	17.1
Environmental Health Hazards Index	71.3	72	49	79	3.7
Low Poverty Index	55.4	54	7	97	23.6
Transportation Costs Index	50.6	50	42	75	6.3
Transit Trips Index	37.3	39	14	69	11.1

Source: HUD AFFH Dataset (AFFHT0006)

Table 5.85 Summary Statistics for Opportunity Indices for RHS-Guaranteed Loans in the Austin-Round Rock MSA (2019)

	Mean	Median	Minimum	Maximum	Standard Deviation
Jobs Proximity Index	24.8	24.2	1.1	56.7	14
School Proficiency Index	48.8	49	2.5	96.6	28.4
Labor Market Engagement Index	58.5	60	3	95	16.9
Environmental Health Hazards Index	71.8	72	53	79	3.4
Low Poverty Index	53.6	50	12	96	23

Transportation Costs Index	50.4	50	42	72	6.5
Transit Trips Index	37.5	39	14	61	10.5

Source: HUD AFFH Dataset (AFFHT0006)

Table 5.86 Summary Statistics for Opportunity Indices for RHS-Guaranteed Loans in McLennan County (2018)

	Mean	Median	Minimum	Maximum	Standard Deviation
Jobs Proximity Index	35.8	38.9	5	73.9	17.5
School Proficiency Index	55.9	59.9	21.7	97.8	25.5
Labor Market Engagement Index	53.6	61	22	87	20.1
Environmental Health Hazards Index	64.5	66	52	78	7.4
Low Poverty Index	51.1	56	6	91	20.4
Transportation Costs Index	10.3	9	7	28	4.1
Transit Trips Index	18.6	11	0	40	16.5

Source: HUD AFFH Dataset (AFFHT0006)

Table 5.87 Summary Statistics for Opportunity Indices for RHS-Guaranteed Loans in McLennan County (2019)

	Mean	Median	Minimum	Maximum	Standard Deviation
Jobs Proximity Index	38.5	41.8	6	73.9	16.8
School Proficiency Index	51.5	55.7	1.2	86.3	23.6
Labor Market Engagement Index	51.9	56.5	11	78	22.1

Environmental Health Hazards Index	63.2	59	47	78	9
Low Poverty Index	47.7	52	6	79	21.8
Transportation Costs Index	11.5	9	5	28	5.4
Transit Trips Index	20.4	13	0	57	18

Source: HUD AFFH Dataset (AFFHT0006)

CHAPTER VI

DERIVING AN IMPROVED INDICATOR OF PURCHASE AFFORDABILITY

Housing planners, policymakers, and practitioners frequently utilize indicators of housing affordability for a myriad of purposes: most obviously, to measure the presence and magnitude of perceived affordability problems, but also to direct housing assistance, procure funding for various programs and initiatives, and compare affordability over time and across geographies (Dokko, 2018). Such indicators, a common feature in planning and policy reports, generally form the basis for the conversation on affordability. However, despite the ubiquity in usage, these indicators broadly fail to provide an adequate means by which to measure affordability (Ezennia & Hoskara, 2019; Haurin, 2016; Jewkes & Delgadillo, 2010; O'Dell et al., 2004; Quigley & Raphael, 2004). This proves particularly problematic, as perceptions of affordability problems (or the lack thereof) may be falsely reaffirmed by measures prone to the over (or under) estimation of the problem: "With no clear measure of housing affordability, policymakers may be unable to develop a systematic understanding of the challenges or may rely too heavily on anecdotes, rather than evidence, to shape their perspectives" (Dokko, 2018, p. 140).

This research seeks to develop an improved indicator of housing affordability to provide housing planners, policymakers, and practitioners another means by which to quantify home purchasing potential. As such, the proposed indicator serves as a measure of *purchase affordability*—that is, it depicts the ability of households (either homeowners or renters) to qualify for mortgage financing (and therefore attain homeownership). The purpose of the indicator is two-fold: 1) to estimate purchase affordability for both conventional and federally-backed mortgages and 2) to estimate household demand for homeownership and the corresponding supply of homes for households across the income distribution. With respect to the former aim, elucidating any potential disparities in purchase affordability among borrowers with federally-backed mortgages may allow planners and policymakers to identify appropriate interventions. Meanwhile, discerning any potential misalignments between supply and demand for particular income cohorts (i.e., identifying the extent of the under- or oversupply of homes within each income cohort) could facilitate more targeted and effective policy initiatives.

The literature review presented a comprehensive overview of the conceptual and methodological limitations of existing definitions and indicators of housing affordability; specifically, owner-occupied housing affordability. Although the limitations will not be reviewed again in this chapter, suffice it to say, the numerous and deep-seated methodological limitations of existing indicators of owner-occupied housing affordability cannot be sufficiently resolved through a single indicator. Rather, scholars and practitioners must continue to address the methodological limitations through several iterations of indicators. As such, this indicator is not intended to be seen as a panacea to the problem of an insufficient indicator of housing affordability; rather, as another stepping stone to the ultimate, ideal indicator. The indicator developed in this dissertation addresses three methodological limitations in particular (Bourassa & Haurin, 2017; Ezennia & Hoskara, 2019; Gan & Hill, 2009; Haurin, 2016; Jewkes & Delgadillo, 2010; O’Dell et al., 2004; Quigley & Raphael, 2004):

1) The lack of an indicator of purchase affordability which a) offers ease and simplicity of computation and interpretation and b) compares household demand for homeownership to the corresponding supply of homes across the income and price distributions, as

opposed to estimating the affordability of the median-priced home for a household earning the median income.

2) The assumption of existing indicators of purchase affordability that borrowers will obtain conventional mortgage financing (although CFPB/HMDA data indicated that federally-backed mortgages represented one-third of all home purchase mortgage originations nationwide in 2019). Moreover, borrowers who qualify for federally-backed mortgages generally denote households of lower income, wealth, and/or credit—i.e., accessing homeownership proves more difficult for these households and remains a top policy priority (Follain, 1990b; LaCour-Little, 2007; Pennington-Cross & Nichols, 2000). Although it is well-known that borrowing constraints vary considerably among households—with significant implications for purchase affordability, existing indicators of purchase affordability do not allow for flexibility in the borrowing constraints and other mortgage financing conditions (Haurin, 2016).

3) The lack of inclusion by existing indicators of the additional costs of both mortgage financing—including private mortgage insurance, upfront and annual mortgage insurance premiums, and annual funding fees—and homeownership—i.e., property taxes and insurance. These costs pose varying effects on purchase affordability, but particularly with respect to lower-priced homes, as the costs comprise a larger portion of the total monthly mortgage payment.

This chapter details the development of an improved indicator of purchase affordability—the Losey Indicator of Purchase Affordability, beginning with a comprehensive overview of the effects of several variables on purchase affordability. An extensive review of the design of the indicator follows, including its assumptions and the methodology derived to quantify household demand for homeownership and the corresponding supply of homes. This chapter concludes with a discussion of the results of the indicator within the three study sites, the strengths and limitations of the indicator, its reliability and validity, and policy implications.

What Affects Purchase Affordability?

Before delving into the methodology behind the improved indicator, it is perhaps helpful to first review the effects of particular variables on purchase affordability. Although a myriad of variables may considerably affect purchase affordability, this section focuses on the primary factors, which fall into one of three categories: 1) the components of mortgage financing (the interest rate, loan term, DTI ratio, and LTV ratio), 2) the costs of mortgage financing (depending on the loan type, private mortgage insurance, upfront and annual mortgage insurance premiums, and annual guarantee & funding fees), and 3) the additional costs of homeownership (property taxes and insurance) (Acolin, Bricker, et al., 2016; Bourassa & Haurin, 2017). This section reviews the effect of changes in these variables on the monthly mortgage payment.

The total monthly mortgage payment acts as a function of several characteristics at the loan and property levels: the loan term (i.e., the length of the loan), mortgage interest rate, mortgage insurance (if applicable; charged on loans with a LTV ratio that exceeds 80%), LTV ratio, and property taxes and insurance (Bourassa & Haurin, 2016; Gaines, 2006). Lenders deem this confluence of loan characteristics as “PITI,” or mortgage principal and interest and property taxes and insurance (Harris, 2002). Lenders generally use the DTI ratio to determine the maximum mortgage payment; in this sense, while the DTI ratio is not directly priced into the total monthly mortgage payment, it is a determinant of the maximum home price affordable to a particular household.

Although the credit score is one of the three primary borrowing constraints used by lenders to determine the creditworthiness of applicants, it is not directly factored into the computation of the total monthly mortgage payment (Acolin, Bricker, et al., 2016; Hunt & Losey, 2020). As such, in deriving the maximum home price affordable to a household of a particular income, it is essential to consider the following six characteristics at the borrower, loan, and property levels: the 1) loan term, 2) mortgage interest rate, 3) additional costs of borrowing, including private mortgage insurance and upfront and annual mortgage insurance premiums, 4) LTV ratio, 5) property taxes and insurance, and 6) DTI ratio (Bourassa & Haurin, 2017). Table 6.1 denotes the effect (i.e., increase or decrease) of an increase in each characteristic on the total monthly mortgage payment and maximum home price affordable.

Table 6.1 The Effects of Characteristics of the Borrower, Loan, or Property on the Total Monthly Mortgage Payment and Maximum Home Price Affordable

Characteristic of the Borrower, Loan, or Property	Effect of Increase on Total Monthly Mortgage Payment (Ceteris Paribus)	Effect of Increase on Maximum Home Price Affordable (Ceteris Paribus)
Loan term	Decrease	Increase
Mortgage interest rate	Increase	Decrease
Additional costs of borrowing	Increase	Decrease
LTV ratio	Increase	Decrease
Property taxes and insurance	Increase	Decrease
DTI ratio	-	Increase

For a home of a particular price, variations in those characteristics can yield significant differences in the monthly mortgage payment. Such a phenomenon complicates the derivation of an indicator which applies a single value for each characteristic (such as the HAI, which uses an

80% LTV ratio, 25% DTI ratio, and the prevailing mortgage interest rate) (Gaines, 2005; Jewkes & Delgadillo, 2010). To compute the effects of changes in each characteristic on the total monthly mortgage payment, several assumptions are made: a loan term of 30 years, mortgage interest rate of 3%, LTV ratio of 80%, property taxes and insurance of 4%, and DTI ratio of 25%, as listed in Table 6.2. (The assumptions do not include mortgage insurance as the LTV ratio does not exceed 80%; however, the effect of mortgage insurance proves similar to increases in the mortgage interest rate).

Table 6.2 Assumptions in Computing the Total Monthly Mortgage Payment

Loan term	30 years
Mortgage interest rate	3%
LTV ratio	80%
Property taxes and insurance	4%
DTI ratio	25%

Effect of Changes in the Loan Term on the Monthly Mortgage Payment

Ceteris paribus, an increase in the loan term decreases the monthly mortgage payment, as depicted in Table 6.3. For example, for a home price of $100,000, provided the assumptions outlined above, the total monthly mortgage payment measures $777 with a loan term of 20 years and $671 with a loan term of 30 years. Purchase affordability increases as the loan term increases.

Table 6.3 The Effect of the Loan Term on the Total Monthly Mortgage Payment

	Loan Term				
Home Price	20	25	30	35	40
$75,000	$583	$535	$503	$481	$465
$100,000	$777	$713	$671	$641	$620
$125,000	$971	$891	$838	$802	$775
$150,000	$1,166	$1,069	$1,006	$962	$930

$175,000	$1,360	$1,247	$1,174	$1,122	$1,085
$200,000	$1,554	$1,425	$1,341	$1,282	$1,239
$225,000	$1,748	$1,604	$1,509	$1,443	$1,394
$250,000	$1,943	$1,782	$1,677	$1,603	$1,549
$275,000	$2,137	$1,960	$1,844	$1,763	$1,704
$300,000	$2,331	$2,138	$2,012	$1,924	$1,859

Effect of Changes in the Mortgage Interest Rate on the Monthly Mortgage Payment

Ceteris paribus, an increase in the mortgage interest rate increases the monthly mortgage payment, as depicted in Table 6.4. For example, for a home price of $100,000, provided the assumptions outlined above, the total monthly mortgage payment measures $671 with an interest rate of 3% and $763 with an interest rate of 5%. Purchase affordability declines as the mortgage interest rate rises.

Table 6.4 The Effect of the Mortgage Interest Rate on the Total Monthly Mortgage Payment

	Interest Rate				
Home Price	3%	3.5%	4%	4.5%	5%
$75,000	$503	$519	$536	$554	$572
$100,000	$671	$693	$715	$739	$763
$125,000	$838	$866	$894	$923	$953
$150,000	$1,006	$1,039	$1,073	$1,108	$1,144
$175,000	$1,174	$1,212	$1,252	$1,293	$1,335
$200,000	$1,341	$1,385	$1,431	$1,477	$1,526
$225,000	$1,509	$1,558	$1,609	$1,662	$1,716
$250,000	$1,677	$1,731	$1,788	$1,847	$1,907
$275,000	$1,844	$1,905	$1,967	$2,031	$2,098
$300,000	$2,012	$2,078	$2,146	$2,216	$2,288

Effect of Changes in the LTV Ratio on the Monthly Mortgage Payment

Ceteris paribus, an increase in the LTV ratio increases the monthly mortgage payment, as depicted in Table 6.5. For example, for a home price of $100,000, provided the assumptions outlined above, the total monthly mortgage payment measures $671 with an LTV ratio of 80% and $747 with an LTV ratio of 98%. Purchase affordability declines as the LTV ratio rises.

Table 6.5 The Effect of the LTV Ratio on the Total Monthly Mortgage Payment

	LTV					
Home Price	80%	90%	95%	96.5%	98%	100%
$75,000	$503	$535	$550	$555	$560	$566
$100,000	$671	$713	$734	$740	$747	$755
$125,000	$838	$891	$917	$925	$933	$944
$150,000	$1,006	$1,069	$1,101	$1,110	$1,120	$1,132
$175,000	$1,174	$1,247	$1,284	$1,295	$1,306	$1,321
$200,000	$1,341	$1,426	$1,468	$1,480	$1,493	$1,510
$225,000	$1,509	$1,604	$1,651	$1,665	$1,680	$1,699
$250,000	$1,677	$1,782	$1,835	$1,850	$1,866	$1,887
$275,000	$1,844	$1,960	$2,018	$2,035	$2,053	$2,076
$300,000	$2,012	$2,138	$2,202	$2,221	$2,240	$2,265

Effect of Changes in Property Taxes and Insurance on the Monthly Mortgage Payment

Ceteris paribus, an increase in property taxes and insurance (i.e., the additional costs of homeownership) increases the monthly mortgage payment, as depicted in Table 6.6. For example, for a home price of $100,000, provided the assumptions outlined above, the total monthly mortgage payment measures $587 when property taxes and insurance measure 3% of home price and $837 when they equate to 6% of home price. Purchase affordability decreases as the additional costs of homeownership increase.

Table 6.6 The Effect of Property Taxes and Insurance on the Total Monthly Mortgage Payment

	Property Taxes and Insurance				
Home Price	3%	4%	5%	6%	7%
$75,000	$440	$503	$565	$628	$690
$100,000	$587	$671	$754	$837	$921
$125,000	$734	$838	$942	$1,047	$1,151
$150,000	$881	$1,006	$1,131	$1,256	$1,381
$175,000	$1,028	$1,174	$1,319	$1,465	$1,611
$200,000	$1,175	$1,341	$1,508	$1,675	$1,841
$225,000	$1,321	$1,509	$1,696	$1,884	$2,071
$250,000	$1,468	$1,677	$1,885	$2,093	$2,302
$275,000	$1,615	$1,844	$2,073	$2,303	$2,532
$300,000	$1,762	$2,012	$2,262	$2,512	$2,762

Design of the Losey Indicator of Purchases Affordability

This indicator quantifies purchase affordability through a comprehensive framework, or model, which relates household demand for homeownership to the corresponding supply of homes. The indicator involves a series of steps which require users to gather publicly-available data and input it into the model. This indicator di6des the series of steps involved in computing purchase affordability into two categories, the first of which involves estimating the household demand for homeownership and the second of which entails estimating the supply of homes. The following sections will delve more deeply into the exact steps involved in the computation of the model.

Assumptions

Several assumptions undergird the development of this indicator of purchase affordability:

1) The vast majority of households in the U.S. require mortgage financing to purchase a home—86% of homebuyers used mortgage financing in 2020 (Oppler, 2020). As such, purchase affordability is a direct function of mortgage financing—specifically, access to mortgage loans and the qualifying standards imposed on borrowers.
2) Borrowing constraints vary considerably among indi6dual households (Duca & Rosenthal, 1994; Linneman & Wachter, 1989). Such diversity— specifically, in the LTV and DTI ratios—diminishes the utility of deri6ng estimates of affordability based on singular values for the LTV and DTI ratios, which fails to represent the entire population of borrowers. Rather, to allow for differentiation in the mortgage financing terms presented by different households, particularly differences along the income distribution, the indicator enables users to select the LTV and DTI ratios most applicable to the problem at hand and the user's specific needs.
3) The additional costs of homeownership—specifically, property taxes and insurance—amount to 4% annually of the home value. Property taxes are assumed to amount to 3% of the home value; property insurance, 1% (Gaines & Losey, 2017). In reality, these costs differ for each property, but without more detailed information, prove difficult to discern on a case-by-case basis.
4) For conventional loans with an LTV ratio which exceeds 80%, private mortgage insurance equals 0.75% of the loan amount. For FHA loans, the upfront mortgage insurance premium equals 1.75% of the loan amount. Meanwhile, the annual mortgage insurance premium varies based on the loan amount, loan term, and LTV ratio. For mortgages with a loan term which exceeds 15 years and a loan amount no greater than

$625,500, the annual mortgage insurance premium equals 0.8% for mortgages with an LTV ratio no greater than 95% and 0.85% otherwise. For mortgages with a loan term which exceeds 15 years and a loan amount greater than $625,500, the annual mortgage insurance premium amounts to 1.0% for loans with an LTV ratio no greater than 95% and 1.05% otherwise. For mortgages with a loan term no greater than 15 years and a loan amount no greater than $625,500, the annual mortgage insurance premium equals 0.45% for mortgages with an LTV ratio no greater than 90% and 0.7% otherwise. For mortgages with a loan term which exceeds 15 years and a loan amount greater than $625,500, the annual mortgage insurance premium equals 0.45% for loans with an LTV ratio no greater than 78%, 0.7% for loans with an LTV ratio between 78% and 90%, and 0.95% for loans with an LTV ratio greater than 0.95% (*Mortgage Credit Analysis for Mortgage Insurance on One- to Four-Unit Mortgage Loans (4155.1) | HUD.Gov / U.S. Department of Housing and Urban Development (HUD)*, n.d.). For VA loans, the funding fee amounts to 2.3% for loans with an LTV ratio greater than 95%, 1.65% for loans with an LTV ratio between 90% and 95%, and 1.4% for loans with an LTV ratio equal to or greater than 10% (*VA Funding Fee and Loan Closing Costs*, 2020). Lastly, for RHS mortgages, the upfront guarantee fee is 1.50% (*Community Facilities Guaranteed Loan Program | Rural Development*, n.d.).

Quantifying Household Demand for Homeownership

Measuring household demand for a housing unit generally proves the primary focus of indicators of housing affordability. However, most indicators utilize either median household income or median family income, as opposed to estimating affordability across the income distribution (Gan & Hill, 2009). This diminishes the ability of those indicators to serve as representative measures of the entire population, particularly in geographies with wider ranges in income (i.e., wider income disparities). Meanwhile, federal housing policy (both homeownership and rental) serves specific income groups—for example, in the instance of the former, federally-backed mortgages generally target low- and moderate-income households (Jones, 2018). Such a practice indicates that incorporating a range of incomes, as opposed to a single figure, will enhance the ability of indicators to measure purchase affordability. The steps presented in this section illustrate the process developed to compute household demand for homeownership within the framework of the improved indicator of purchase affordability.

Step 1: Collect Income Figures

Federal housing policy determines household eligibility for a variety of its programs on the basis of income. In the instance of subsidized rental units, the federal government categorizes households into one of three income cohorts to determine eligibility for rental assistance (*Income Limits | HUD USER*, n.d.):

1) Extremely Low-Income households, which earn no more than 30% of area median family income,
2) Very Low-Income households, which earn between 31% and 50% of area median family income, and
3) Low-Income households, which earn between 51% and 80% of area median family income.

Federally-backed mortgages, such as RHS mortgages, tend to target households earning between 80% and 115% of area median income (*Single Family Housing Guaranteed Loan Program | Rural Development*, n.d.). As such, this research incorporates a fourth category:

4) Moderate-Income households, which earn between 80% and 115% of area family income.

Homeownership is generally unattainable for the lowest-income households (particularly Extremely Low-Income households), who tend to present insufficient income, wealth, and/or credit (i.e., creditworthiness), and therefore typically cannot access conventional mortgage financing. Moreover, these households may still encounter difficulty in attaining financing for a federally-backed mortgage. As such, it is expected that homeownership will largely prove “out of reach” to Extremely Low-Income households.

However, users of the indicator may choose to impose different income thresholds. For example, users of the indicator who work in the public or non-profit sectors may be more interested in affordability for lower-income homebuyers, while users of the indicator who work in the private sector will likely be more vested in pro6ding opportunities for homeownership to moderate and higher-income buyers. Furthermore, the indicator does not invoke a limit as to the number of income thresholds. Users may choose to compute affordability for as many income thresholds as desired. Moreover, users seeking to capture racial and/or ethnic disparities in purchase affordability could compute several iterations of the indicator to reflect income figures for households of different races and ethnicities. Users can also customize the geographic boundaries of the indicator—from the nation to the block group.

Table 6.7 lists the median family income for each study site in 2018 and 2019. The median family income depicted considerable discrepancies across the three study sites, ranging from $53,700 to $95,900. Meanwhile, Tables 6.8 and 6.9 portray the income range for each cohort across the three study sites in 2018 and 2019, respectively. The income range for Extremely Low-Income households remains consistent across the three study sites, but the other income cohorts portray substantial differences.

Table 6.7 Median Family Income in the Study Sites

Income Cohort	2018	2019
Anderson County	$53,700	$55,700
Austin-Round Rock MSA	$86,000	$95,900
McLennan County	$60,000	$64,500

Source: HUD Income Limits

Table 6.8 2018 Income Figures for the Study Sites

Income Cohort	Income Range	Anderson County	Austin-Round Rock MSA	McLennan County
Extremely Low-Income	0-30%	$0 - $25,100	$0 - $25,800	$0 - $25,100
Very Low-Income	>30-50%	$25,101 - $28,250	$25,801 - $43,000	$25,101 - $30,000
Low-Income	>50-80%	$28,251 - $45,200	$43,001 - $68,800	$30,001 - $48,000
Moderate-Income	>80-115%	$45,201 - $61,755	$68,800 - $98,900	$48,001 - $69,000

Source: HUD Income Limits

Table 6.9 2019 Income Figures for the Study Sites

Income Cohort	Income Range	Anderson County	Austin-Round Rock MSA	McLennan County
Extremely Low-Income	0-30%	$0 - $25,750	$0 - $28,400	$0 - $25,750
Very Low-Income	>30-50%	$25,751 - $29,350	$28,401 - $47,300	$25,751 - $32,250

Low-Income	>50-80%	$29,351 - $46,950	$47,301 - $75,500	$32,251 - $51,600
Moderate-Income	>80-115%	$46,951 - $64,055	$75,501 - $110,285	$51,601 - $74,175

Source: HUD Income Limits

Step 2: Impute the Proportion of Households in Each Income Cohort

Using publicly-available data from the American Community Survey (ACS), one can impute the proportion of households within each income range. As this research focuses specifically on quantifying purchase affordability for first-time buyers, it imputes the proportion of households in each income cohort based on the income distribution of renter-occupied households. However, users may also choose to calculate this proportion based on the income distribution of owner-occupied households, or both owner- and renter-occupied households.

In essence, this step seeks to remedy the issue of encountering income cohorts whose values do not align evenly with publicly-available income data, such as that from the ACS. For example, ACS income data generally presents itself in set, even increments, such as $5,000, $10,000, $15,000, etc, as depicted in Table 6.10. However, the values for the income cohorts as determined by HUD generally do not match the increments imposed in the ACS data. The income range for Very Low-Income households in Anderson County equals $25,751-$29,350 in 2019. Meanwhile, the closest corresponding income bin in the ACS data ranges from $25,000 to $34,999. This indicates users must impute the proportion of households earning between $25,751 and $29,350.

The following computation for Anderson County pro6des an example of the methodology adopted by this indicator to impute the proportion of households within each income cohort:

To impute the number of households in the Extremely Low-Income cohort, one would add the number of renter-occupied households for households earning up to $24,999. Then, one would impute the number of households earning between $25,000 and $25,750. The equation for such a computation equals the income figure of interest ($25,750) minus the lower end of the income range (i.e., $25,000), di6ded by the difference between the upper and lower ends of that income range (i.e., $34,999 - $25,000), multiplied by the number of households within the $25,000-$34,999 income range. Table 6.11 depicts the imputation for all four income cohorts.

Both the lower and upper ends of the income range for Very Low-Income households ($25,751-$29,350) lie within the same field in the ACS data ($25,000-$34,999). As such, the number of renter-occupied households in this income cohort equals the difference between the proportion of renter-occupied households within that field earning the higher figure—$29,350 (43.5%)—and the proportion of such households within that field earning the lower figure—$25,751 (7.5%), multiplied by the number of renter-occupied households earning between $25,000 and $34,999 (871).

Meanwhile, to impute the number of renter-occupied households in the Low-Income cohort, one would multiply the imputed proportion of renter-occupied households earning between $29,350 and $34,999 (i.e., 100%-43.5%, or 56.5%) by the total number of renter-occupied households in that field. Then, one would multiply the imputed proportion of renter-occupied households earning between $35,000 and $46,960 (79.7%) by the total number of renter-occupied households in that field. The sum of the two figures equals the imputed number of renter-occupied households within the Low-Income cohort.

Finally, to impute the number of renter-occupied households in the Moderate-Income cohort, one would multiply the imputed proportion of renter-occupied households earning between $46,950 and $49,999 (i.e., 100%-79.7%, or 20.3%) by the number of households within that field. Then, one would multiply the imputed proportion of renter-occupied households earning between $50,000 and $74,999 (56.2%) by the number of households within that field. The sum of the two figures equals the imputed number of renter-occupied households within the Moderate-Income cohort.

Table 6.10 Household Income in Anderson County in 2019

Household Income	Number of Renter-Occupied Households
Less than $5,000	185
$5,000 to $9,999	271
$10,000 to $14,999	498
$15,000 to $19,999	436
$20,000 to $24,999	418
$25,000 to $34,999	871
$35,000 to $49,999	894
$50,000 to $74,999	905
$75,000 to $99,999	411
$100,000 to $149,999	162
$150,000 or more	20

Source: U.S. Census Bureau (American Community Survey)

Table 6.11 Imputation of the Number of Renter-Occupied Households in Each Cohort, Anderson County (2019)

Income Cohort	Income Range	Imputation	
Extremely Low-Income	$0 - $25,750	($25,750 - $25,000) / ($34,999 - $25,000) = 7.5%	185 + 271 + 498 + 436 + 418 + 871 *(7.5%) = 1,873

Very Low-Income	$25,751 - $29,350	($29,350 - $25,000) / ($34,999 - $25,000) = 43.5%	871*(43.5%) – 871*(7.5%) = 314
Low-Income	$29,351 - $46,950	($46,950 - $35,000) / ($49,999 - $35,000) = 79.7%	871*(100%-43.5%) + 894*(79.7%) = 1,204
Moderate-Income	$46,951 - $64,055	($64,055 - $50,000) / ($74,999 - $50,000) = 56.2%	894*(100%-79.7%) + 905*(56.2%) = 691

Source: U.S. Census Bureau (American Community Survey)

Step 3: Determine the Proportion of Households Within Each Income Cohort

This step entails one simple computation: di6de the number of imputed households within each income cohort (calculated in step 2) by the total population of households in the geography of interest. This figure represents the proportion of households within each income cohort.

Quantifying the Supply of Homes

An indicator of purchase affordability which quantifies the demand for homeownership proves of little utility to its users without an accompanying comparison to the supply of homes. After all, knowing how much households can afford to devote to homeownership (i.e., the maximum home price affordable to them) matters little without corresponding knowledge of how many homes are available to households within that price range. However, existing indicators generally paint an incomplete picture of purchase affordability by failing to relate household demand for homeownership to the supply of homes. The popular indicators of purchase affordability—in particular, the Median Multiple and HAI—ostensibly use median home price as a supply-side measure of owner-occupied housing units. However, while median home price certainly bears a strong correlation with the supply of homes, prices are also informed by a number of other factors, such as locational attributes, which are not explicated by the indicators. Moreover, using the median home price, as opposed to the distribution of homes, proves particularly problematic in estimating affordability for lower-income cohorts, for whom attaining mortgage financing for the median-priced home may not be possible.

This section pro6des an over6ew of the steps involved in estimating the supply of homes affordable to predetermined income cohorts. Specifically, this section describes—in detail—one particular way to derive the supply of homes affordable to various income cohorts. Although this methodology proves more cumbersome in both computation and interpretation than that of other indicators, it also allows users to arrive at a measure of affordability which is more representative of lower-income cohorts.

Step 1: Collect Data on the Home Price Distribution

Several publicly-available sources pro6de data on the price distribution of homes. For example, the U.S. Census Bureau pro6des the count of homes within specific value ranges in the American Community Survey. The Census Bureau also publishes counts of new homes sold by sales price on a quarterly and annual basis for the nation. The Texas Real Estate Research Center publishes the price distribution of homes (i.e., the number of homes sold within particular price ranges) on an annual basis at the state, MSA, county, and local market area levels (only for geographies in Texas). This research uses the lattermost source of data since all geographies of interest lie in Texas.

Step 2. Compute the Home Price-to-Income Multiplier

The home price-to-income multiplier developed in this research closely resembles the Median Multiple, one of the most popular indicators of purchase affordability, in that it relates home price to income. However, several significant differences emerge: instead of inputting the median home price and median household income for a particular geography, the multiplier computes the maximum home price affordable for a household of a particular income. In other words, this multiplier calculates purchase affordability across the home price and income distributions. Furthermore, instead of imposing arbitrary constraints on the maximum home price affordable to a particular household (i.e., the Median Multiple stipulates that a multiple which exceeds 3.0 indicates a home is unaffordable), the home price-to-income multiplier uses mortgage loan origination data to derive a figure representative of the actual home price-to-income ratio, as opposed to an assumed threshold.

The multiplier uses a variety of variables, including 1) mortgage financing terms—the mortgage interest rate, loan term, LTV ratio, DTI ratio, 2) the costs of mortgage financing—private mortgage insurance, the upfront and annual mortgage insurance premiums, and annual funding fees, and 3) the additional costs of homeownership—property taxes and insurance. Depending on the type of loan, the formula for the multiplier deducts the costs of the FHA upfront fee and FHA annual fee, VA funding fee, or RHS funding fee from the price of the home and di6des this amount by the total monthly mortgage payment, which incorporates private mortgage insurance (if applicable) into the mortgage interest rate and the costs of property taxes and insurance. Specifically, the formula is as follows:

Home price-to-income multiplier = (1 – (1*FHA upfront fee*LTV) – (1*FHA annual fee*LTV) – (1*VA funding fee*LTV) – (1*RHS funding fee*LTV)) / (((PMT((mortgage interest rate + private mortgage insurance)/12, loan term(in months), -LTV) + (property taxes and insurance/12))/DTI)*12). Users may download a spreadsheet that automatically computes the multiplier (and the results for the model) from https://clare-losey.github.io/dissertation/.

One can observe that differences in the home price-to-income multiplier significantly affect the maximum home price affordable to a particular household, as depicted in Table 6.12. As the home price-to-income multiplier increases, the maximum affordable home price increases. For example, a household earning $40,000 can afford a maximum home price of $80,000 based on a multiplier of 2 but $240,000 based on a multiplier of 6. This represents a $160,000 differential in the maximum home price affordable to that household. Although the likelihood of obtaining a mortgage loan decreases as the home price-to-income multiplier increases (due to the increase in borrower risks borne by the lender), the multiplier of borrowers with federally-backed mortgages will generally be higher than that of borrowers who obtain conventional mortgage financing.

Table 6.12 The Maximum Home Price Affordable Based on Household Income

	Home Price-to-Income Multiplier				
Household Income	2	3	4	5	6
$25,000	$50,000	$75,000	$100,000	$125,000	$150,000
$30,000	$60,000	$90,000	$120,000	$150,000	$180,000
$35,000	$70,000	$105,000	$140,000	$175,000	$210,000
$40,000	$80,000	$120,000	$160,000	$200,000	$240,000
$45,000	$90,000	$135,000	$180,000	$225,000	$270,000

$50,000	$100,000	$150,000	$200,000	$250,000	$300,000
$55,000	$110,000	$165,000	$220,000	$275,000	$330,000
$60,000	$120,000	$180,000	$240,000	$300,000	$360,000
$65,000	$130,000	$195,000	$260,000	$325,000	$390,000
$70,000	$140,000	$210,000	$280,000	$350,000	$420,000

Step 3. Calculate the Maximum Home Price Affordable to Each Income Cohort

Once the user of the indicator computes the home price-to-income multiplier, the next step entails calculating the maximum home price affordable to each income cohort. The range in the maximum affordable home price simply equals the multiplier multiplied by the lower and upper ends of the income range. For instance, pro6ded a multiplier of 3 and lower and upper ends of the income range for a particular cohort of $25,751 and $29,350, the maximum home price affordable to that cohort would range from $25,751*3 ($77,253) to $29,350*3 ($88,050).

Step 4: Impute the Number of Homes Affordable to Each Income Cohort

The methodology for this step mimics that of step 2 in the pre6ous section (i.e., "Impute the Proportion of Households in Each Income Cohort"). As such, it will not be re6ewed here. The only difference lies in the data—instead of income data, this imputation involves either home price data from the Texas Real Estate Research Center or home value data from the U.S. Census Bureau (American Community Survey).

Step 5: Determine the Proportion of Homes Affordable to Each Price Cohort

This step entails one simple calculation: di6de the number of imputed homes within each price cohort (calculated in step 4) by the total population of homes in the geography of interest. This figure represents the proportion of homes within each price cohort.

Step 6: Determine the Over (or under) Supply of Homes Affordable to Each Income Cohort

Subtract the proportion of renter-occupied households within a particular income cohort (i.e., the figure obtained in step 3 in the pre6ous section, “Determine the Proportion of Households Within Each Income Cohort”) from the proportion of homes affordable to that income cohort (i.e., the pre6ous step in this section, “Determine the Proportion of Homes Affordable to Each Price Cohort”). The result equals the proportion of homes either over- or under-supplied within each income and price cohort.

Quantifying Purchase Affordability

This section discusses the results of the indicator in 2018 and 2019 for renter-occupied households within the three study sites—Anderson County, McLennan County, and the Austin-Round Rock MSA—as well as the interpretations and implications of those results. Overarchingly, several patterns emerge from the three study sites:

- In the Austin-Round Rock MSA and McLennan County, regardless of loan type, demand significantly outpaces the supply of homes affordable to the lowest-income renters—Extremely Low-Income households, which earn 30% or less of median family income—indicating homeownership is largely out of reach for these households.
- As the home price-to-income multiplier increases, the proportion of homes affordable to lower-income cohorts also increases, reducing supply constraints, particularly for Very-Low-Income households (those earning up to 50% of area median income).

- Easing (i.e., decreasing) the borrowing constraints enhances purchase affordability, particularly for Very Low-Income households, by increasing the supply of homes affordable to them.

Anderson County

The median values for the home price-to-income multiplier in Anderson County range from 3.12 to 3.86 in 2018 and 3.78 to 3.94 in 2019. As depicted in Tables 6.13 and 6.16, the median values for the multiplier are higher for FHA-insured and VA-guaranteed loans and lower for conventional and RHS-guaranteed loans. Meanwhile, Tables 6.14 and 6.17 portray the maximum home price affordable at varying income levels based on the median value of each multiplier. For example, for a household earning $30,000 and seeking a conventional loan, the multiplier amounted to 3.32 and 3.78 in 2018 and 2019, respectively, for a maximum affordable home price of $93,600 and $113,400, respectively. Lastly, Tables 6.15 and 6.18 depict the range in the home price affordable to each income cohort by loan type in 2018 and 2019. For example, Very Low-Income households seeking a conventional loan could afford a home priced between $83,308 and $93,672 in 2018.

Table 6.13 Home Price-to-Income Multiplier in Anderson County (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
25^{th} Percentile	2.67	3.26	2.47	2.37
Median	3.32	3.86	3.77	3.12
75^{th} Percentile	4.17	4.54	4.75	3.24

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 6.14 Maximum Home Price Affordable in Anderson County (2018)

	Home Price-to-Income Multiplier			
Household Income	3.12	3.32	3.77	3.86
$20,000	$62,400	$66,400	$75,400	$77,200
$25,000	$78,000	$83,000	$94,250	$96,500
$30,000	$93,600	$99,600	$113,100	$115,800
$35,000	$109,200	$116,200	$131,950	$135,100
$40,000	$124,800	$132,800	$150,800	$154,400
$45,000	$140,400	$149,400	$169,650	$173,700
$50,000	$156,000	$166,000	$188,500	$193,000
$55,000	$171,600	$182,600	$207,350	$212,300
$60,000	$187,200	$199,200	$226,200	$231,600
$65,000	$202,800	$215,800	$245,050	$250,900
$70,000	$218,400	$232,400	$263,900	$270,200
$75,000	$234,000	$249,000	$282,750	$289,500
$80,000	$249,600	$265,600	$301,600	$308,800

Table 6.15 The Affordable Home Price Range in Anderson County (2018)

Income Cohort	Income Range	Home Price Range: Conventional	Home Price Range: FHA	Home Price Range: VA	Home Price Range: RHS
Extremely Low-Income	$0 - $25,100	$0 - $83,307	$0 - $96,992	$0 - $94,531	$0 - $78,357
Very Low-Income	$25,101 - $28,250	$83,308 - $93,762	$96,993 - $109,164	$94,532 - $106,395	$78,358 - $88,191
Low-Income	$28,251 - $45,200	$93,763 - $150,018	$109,165 - $174,663	$106,396 - $170,231	$88,192 - $141,106
Moderate Income	$45,201 - $61,755	$150,019 - $204,964	$174,664 - $238,635	$170,232 - $232,580	$141,107 - $192,788

Source: American Community Survey, HUD Income Limits

Table 6.16 Home Price-to-Income Multiplier in Anderson County (2019)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
25th Percentile	2.91	3.23	3.20	3.24
Median	3.78	3.94	3.90	3.81

75th Percentile	4.34	4.88	5.06	3.99

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 6.17 Maximum Home Price Affordable in Anderson County (2019)

	Home Price-to-Income Multiplier			
Household Income	3.78	3.81	3.90	3.94
$20,000	$75,600	$76,200	$78,000	$78,800
$25,000	$94,500	$95,250	$97,500	$98,500
$30,000	$113,400	$114,300	$117,000	$118,200
$35,000	$132,300	$133,350	$136,500	$137,900
$40,000	$151,200	$152,400	$156,000	$157,600
$45,000	$170,100	$171,450	$175,500	$177,300
$50,000	$189,000	$190,500	$195,000	$197,000
$55,000	$207,900	$209,550	$214,500	$216,700
$60,000	$226,800	$228,600	$234,000	$236,400
$65,000	$245,700	$247,650	$253,500	$256,100
$70,000	$264,600	$266,700	$273,000	$275,800
$75,000	$283,500	$285,750	$292,500	$295,500
$80,000	$302,400	$304,800	$312,000	$315,200

Table 6.18 The Affordable Home Price Range in Anderson County (2019)

Income Cohort	Income Range	Home Price Range: Conventional	Home Price Range: FHA	Home Price Range: VA	Home Price Range: RHS
Extremely Low-Income	$0 - $25,100	$0 - $97,281	$0 - $101,448	$0 - $100,308	$0 - $98,234
Very Low-Income	$25,101 - $28,250	$97,282 - $110,882	$101,449 - $115,631	$100,309 - $114,331	$98,235 - $111,968
Low-Income	$28,251 - $45,200	$110,883 - $177,373	$115,632 - $184,970	$114,332 - $182,891	$111,969 - $179,110
Moderate Income	$45,201 - $61,755	$177,374 - $241,994	$184,971 - $252,359	$182,892 - $249,523	$179,111 - $244,364

Source: American Community Survey, HUD Income Limits

Tables 6.19 and 6.20 portray the results of the indicator for Anderson County in 2018 and 2019. Overall, demand and supply appear to be relatively balanced; in all but one income cohort—Extremely Low-Income households—the difference between supply and demand approximates zero. However, broadly speaking, Very Low-Income, Low-Income, and Moderate-Income households witnessed a slight undersupply of homes across all four loan types in 2018 and 2019. The lowest income cohort (Extremely Low-Income households) depicted a substantial oversupply of homes, indicative of the high share of lower-priced homes in Anderson County. In fact, over one-third of homes in Anderson County were priced under $100,000 in 2018 and 2019 (40.6% and 34.2%, respectively).

Table 6.19 Results of the Indicator in Anderson County (2018)

Income Cohort	Income Range	Demand	Over(under) supply: Conventional	Over(under) supply: FHA	Over(under) supply: VA	Over(under) supply: RHS
Extremely Low-Income	$0 - $25,100	37.8%	6.1%	14.1%	12.7%	3.2%
Very Low-Income	$25,101 - $28,250	5.7%	0.4%	-0.7%	-0.2%	0.1%
Low-Income	$28,251 - $45,200	23.5%	-2.3%	-2.9%	-3.1%	-2.2%
Moderate Income	$45,201 - $61,755	12.8%	0.4%	-2.9%	-2.3%	1.2%

Source: American Community Survey, HUD Income Limits, CFPB/HMDA Dynamic National Loan-Level Dataset

Table 6.20 Results of the Indicator in Anderson County (2019)

Income Cohort	Income Range	Demand	Over(under) supply: Conventional	Over(under) supply: FHA	Over(under) supply: VA	Over(under) supply: RHS
Extremely Low-Income	$0 - $25,750	36.9%	10.6%	12.7%	12.3%	11.2%
Very Low-Income	$25,751 - $29,350	6.2%	-0.9%	-1.2%	-1.3%	-1.0%

Income Cohort	Income Range	Demand	Over(under) supply: Conventional	Over(under) supply: FHA	Over(under) supply: VA	Over(under) supply: RHS
Low-Income	$29,351 - $46,950	23.7%	-2.6%	-2.1%	-2.2%	-2.5%
Moderate Income	$46,951 - $64,055	13.6%	-2.7%	-3.6%	-3.4%	-2.9%

Source: American Community Survey, HUD Income Limits, CFPB/HMDA Dynamic National Loan-Level Dataset

Austin-Round Rock MSA

The median values for the home price-to-income multiplier in the Austin-Round Rock MSA vary from 3.64 to 4.5 in 2018 and 3.88 to 4.62 in 2019. As depicted in Tables 6.21 and 6.24, the median values for the multiplier are higher for FHA-insured and VA-guaranteed loans and lower for conventional and RHS-guaranteed loans. Meanwhile, Tables 6.22 and 6.25 portray the maximum home price affordable at varying income levels based on the median value of each multiplier. For example, for a household earning $30,000 and seeking a conventional loan, the multiplier amounted to 3.87 and 3.89 in 2018 and 2019, respectively, for a maximum affordable home price of $109,200 and $116,400, respectively. Lastly, Tables 6.23 and 6.26 depict the range in the home price affordable to each income cohort by loan type in 2018 and 2019. For example, Very Low-Income households seeking a conventional loan could afford a home priced between $99,824 and $166,372 in 2018.

Table 6.21 Home Price-to-Income Multiplier in the Austin-Round Rock MSA (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed

25th Percentile	3.12	3.88	3.65	3.22
Median	3.87	4.50	4.34	3.64
75th Percentile	4.56	5.19	5.23	3.93

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 6.22 Maximum Home Price Affordable in the Austin-Round Rock MSA (2018)

	Home Price-to-Income Multiplier			
Household Income	3.64	3.87	4.34	4.50
$20,000	$72,800	$77,400	$86,800	$90,000
$25,000	$91,000	$96,750	$108,500	$112,500
$30,000	$109,200	$116,100	$130,200	$135,000
$35,000	$127,400	$135,450	$151,900	$157,500
$40,000	$145,600	$154,800	$173,600	$180,000
$45,000	$163,800	$174,150	$195,300	$202,500
$50,000	$182,000	$193,500	$217,000	$225,000
$55,000	$200,200	$212,850	$238,700	$247,500
$60,000	$218,400	$232,200	$260,400	$270,000
$65,000	$236,600	$251,550	$282,100	$292,500
$70,000	$254,800	$270,900	$303,800	$315,000
$75,000	$273,000	$290,250	$325,500	$337,500
$80,000	$291,200	$309,600	$347,200	$360,000

Table 6.23 The Affordable Home Price Range in the Austin-Round Rock MSA (2018)

Income Cohort	Income Range	Home Price Range: Conventional	Home Price Range: FHA	Home Price Range: VA	Home Price Range: RHS
Extremely Low-Income	$0 - $25,800	$0 - $99,823	$0 - $115,989	$0 - $112,062	$0 - $93,829
Very Low-Income	$25,801 - $43,000	$99,824 - $166,372	$115,990 - $193,315	$112,063 - $186,770	$93,830 - $156,381
Low-Income	$43,001 - $68,800	$166,373 - $266,196	$193,316 - $309,303	$186,771 - $298,833	$156,382 - $250,210
Moderate Income	$68,801 - $98,900	$266,197 - $382,656	$309,304 - $444,624	$298,834 - $429,572	$250,211 - $359,677

Source: American Community Survey, HUD Income Limits

Table 6.24 Home Price-to-Income Multiplier in the Austin-Round Rock MSA (2019)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
25^{th} Percentile	3.07	3.92	3.68	3.39
Median	3.89	4.62	4.48	3.88
75^{th} Percentile	4.62	5.34	5.38	4.23

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 6.25 Maximum Home Price Affordable in the Austin-Round Rock MSA (2019)

	Home Price-to-Income Multiplier			
Household Income	3.88	3.89	4.48	4.62
$20,000	$77,600	$77,800	$89,600	$92,400
$25,000	$97,000	$97,250	$112,000	$115,500
$30,000	$116,400	$116,700	$134,400	$138,600
$35,000	$135,800	$136,150	$156,800	$161,700
$40,000	$155,200	$155,600	$179,200	$184,800
$45,000	$174,600	$175,050	$201,600	$207,900
$50,000	$194,000	$194,500	$224,000	$231,000
$55,000	$213,400	$213,950	$246,400	$254,100
$60,000	$232,800	$233,400	$268,800	$277,200
$65,000	$252,200	$252,850	$291,200	$300,300
$70,000	$271,600	$272,300	$313,600	$323,400
$75,000	$291,000	$291,750	$336,000	$346,500
$80,000	$310,400	$311,200	$358,400	$369,600

Table 6.26 The Affordable Home Price Range in the Austin-Round Rock MSA (2019)

Income Cohort	Income Range	Home Price Range: Conventional	Home Price Range: FHA	Home Price Range: VA	Home Price Range: RHS
Extremely Low-Income	$0 - $28,400	$0 - $110,390	$0 - $131,346	$0 - $127,204	$0 - $110,094
Very Low-Income	$28,401 - $47,300	$110,391 - $183,854	$131,347 - $218,757	$127,205 - $211,857	$110,095 - $183,360
Low-Income	$47,301 - $75,500	$183,855 - $293,467	$218,758 - $349,178	$211,858 - $338,165	$183,361 - $292,678
Moderate Income	$75,501 - $110,285	$293,468 - $428,676	$349,179 - $510,054	$338,166 - $493,967	$292,679 - $427,524

Source: American Community Survey, HUD Income Limits, CFPB/HMDA Dynamic National Loan-Level Dataset

Tables 6.27 and 6.28 portray the results of the indicator for the Austin-Round Rock MSA in 2018 and 2019. Overall, demand and supply appear to be the least balanced for Extremely Low-Income households, with demand considerably outpaced supply across all four loan types in 2018 and 2019. Demand slightly outpaced supply for Very Low-Income households. Meanwhile, low- and Moderate-Income households witnessed a slight oversupply of homes. Overall, the results indicate that the two lowest income cohorts, but particularly Extremely Low-Income households, experienced difficulty in attaining homeownership due to the lack of sufficient supply to meet household demand.

Table 6.27 Results of the Indicator in the Austin-Round Rock MSA (2018)

Income Cohort	Income Range	Demand	Over(under) supply: Conventional	Over(under) supply: FHA	Over(under) supply: VA	Over(under) supply: RHS
Extremely Low-Income	$0 - $25,800	24.3%	-16.1%	-13.2%	-13.9%	-16.6%
Very Low-Income	$25,801 - $43,000	19.1%	-5.3%	-0.1%	-1.4%	-7.7%
Low-Income	$43,001 - $68,800	23.2%	5.9%	7.5%	7.6%	5.1%
Moderate Income	$68,801 - $98,900	16.2%	5.4%	2.8%	3.2%	5.4%

Source: American Community Survey, HUD Income Limits, CFPB/HMDA Dynamic National Loan-Level Dataset

Table 6.28 Results of the Indicator in the Austin-Round Rock MSA (2019)

Income Cohort	Income Range	Demand	Over(under) supply: Conventional	Over(under) supply: FHA	Over(under) supply: VA	Over(under) supply: RHS
Extremely Low-Income	$0 - $25,100	25.3%	-16.6%	-13.7%	-14.3%	-16.7%
Very Low-Income	$25,101 - $28,250	19.9%	-5.8%	1.1%	-0.4%	-5.9%
Low-Income	$28,251 - $45,200	23.9%	6.3%	6.9%	7.1%	6.3%
Moderate Income	$45,201 - $61,755	14.4%	8.1%	5.5%	6.4%	8.1%

Source: American Community Survey, HUD Income Limits, CFPB/HMDA Dynamic National Loan-Level Dataset

McLennan County

As depicted in Tables 6.29 and 6.32, the median values for the home price-to-income multiplier in McLennan County range from 3.29 to 4.35 in 2018 and 3.69 to 4.3 in 2019. The median values for the multiplier measured higher for FHA-insured and VA-guaranteed loans and lower for conventional and RHS-guaranteed loans. Meanwhile, Tables 6.30 and 6.33 portray the maximum home price affordable at varying income levels based on the median value of each multiplier. For example, for a household earning $30,000 and seeking a conventional loan, the multiplier amounted to 3.29 and 3.69 in 2018 and 2019, respectively, for a maximum affordable home price of $98,700 and $110,700, respectively. Lastly, Tables 6.31 and 6.34 depict the range in the home price affordable to each income cohort by loan type in 2018 and 2019. For example, Very Low-Income households seeking a conventional loan could afford a home priced between $91,891 and $109,828 in 2018.

Table 6.29 Home Price-to-Income Multiplier in McLennan County (2018)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
25th Percentile	2.88	3.56	3.51	3.01
Median	3.66	4.35	4.24	3.29
75th Percentile	4.36	5.11	5.09	3.76

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 6.30 Maximum Home Price Affordable in McLennan County (2018)

	Home Price-to-Income Multiplier			
Household Income	3.29	3.66	4.24	4.35
$20,000	$65,800	$73,200	$84,800	$87,000
$25,000	$82,250	$91,500	$106,000	$108,750
$30,000	$98,700	$109,800	$127,200	$130,500
$35,000	$115,150	$128,100	$148,400	$152,250
$40,000	$131,600	$146,400	$169,600	$174,000
$45,000	$148,050	$164,700	$190,800	$195,750
$50,000	$164,500	$183,000	$212,000	$217,500
$55,000	$180,950	$201,300	$233,200	$239,250
$60,000	$197,400	$219,600	$254,400	$261,000
$65,000	$213,850	$237,900	$275,600	$282,750
$70,000	$230,300	$256,200	$296,800	$304,500
$75,000	$246,750	$274,500	$318,000	$326,250
$80,000	$263,200	$292,800	$339,200	$348,000

Table 6.31 The Affordable Home Price Range (2018)

Income Cohort	Income Range	Home Price Range: Conventional	Home Price Range: FHA	Home Price Range: VA	Home Price Range: RHS
Extremely Low-Income	$0 - $25,100	$0 -$91,890	$0 -$109,230	$0 - $106,512	$0 - $82,475
Very Low-Income	$25,101 - $30,000	$91,891 - $109,828	$109,231 - $130,554	$106,513 - $127,305	$82,476 - $98,576
Low-Income	$30,001 - $48,000	$109,829 - $175,726	$130,555 - $208,886	$127,306 - $203,688	$98,577 - $157,722
Moderate Income	$48,001 - $69,000	$175,727 - $252,605	$208,887 - $300,273	$203,689 - $292,802	$157,723 - $226,725

Source: American Community Survey, HUD Income Limits

Table 6.32 Home Price-to-Income Multiplier in McLennan County (2019)

	Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
25th Percentile	2.91	3.53	3.48	3.29
Median	3.69	4.30	4.20	3.92
75th Percentile	4.44	4.98	5.05	4.20

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 6.33 Maximum Home Price Affordable in McLennan County (2019)

	Home Price-to-Income Multiplier			
Household Income	3.69	3.92	4.20	4.30
$20,000	$73,800	$78,400	$84,000	$86,000
$25,000	$92,250	$98,000	$105,000	$107,500
$30,000	$110,700	$117,600	$126,000	$129,000
$35,000	$129,150	$137,200	$147,000	$150,500
$40,000	$147,600	$156,800	$168,000	$172,000
$45,000	$166,050	$176,400	$189,000	$193,500
$50,000	$184,500	$196,000	$210,000	$215,000
$55,000	$202,950	$215,600	$231,000	$236,500
$60,000	$221,400	$235,200	$252,000	$258,000
$65,000	$239,850	$254,800	$273,000	$279,500
$70,000	$258,300	$274,400	$294,000	$301,000
$75,000	$276,750	$294,000	$315,000	$322,500
$80,000	$295,200	$313,600	$336,000	$344,000

Table 6.34 The Affordable Home Price Range (2019)

Income Cohort	Income Range	Home Price Range: Conventional	Home Price Range: FHA	Home Price Range: VA	Home Price Range: RHS
Extremely Low-Income	$0 - $28,400	$0 - $94,947	$0 - $110,679	$0 - $108,149	$0 - $100,873
Very Low-Income	$28,401 - $47,300	$94,948 - $118,914	$110,680 - $138,618	$108,150 - $135,449	$100,874 - $126,336
Low-Income	$47,301 - $75,500	$118,915 - $190,263	$138,619 - $221,788	$135,450 - $216,718	$126,337 - $202,138

Moderate Income	$75,501 - $110,285	$190,264 - $273,503	$221,789 - $318,820	$216,719 - $311,532	$202,139 - $290,573

Source: American Community Survey, HUD Income Limits

Tables 6.35 and 6.36 portray the results of the indicator for McLennan County in 2018 and 2019. In both years and across all four loan types, Extremely Low-Income households witnessed an undersupply of homes affordable to them. This indicates that attaining homeownership proves particularly challenging for Extremely Low-Income households in McLennan County in 2018 and 2019. The magnitude of the undersupply ranges from -3.0% to -16.2%, measuring the highest for households seeking RHS-guaranteed loans. Meanwhile, the other income cohorts depict an oversupply of homes affordable to them; the magnitude of the oversupply measures the highest among Low-Income households.

Table 6.35 Results of the Indicator for McLennan County (2018)

Income Cohort	Income Range	Demand	Over(under) supply: Conventional	Over(under) supply: FHA	Over(under) supply: VA	Over(under) supply: RHS
Extremely Low-Income	$0 - $25,100	42.9%	-11.1%	-3.0%	-4.2%	-16.2%
Very Low-Income	$25,101 - $30,000	6.9%	1.5%	1.9%	1.7%	1.7%
Low-Income	$30,001 - $48,000	20.0%	5.3%	6.7%	7.0%	4.0%
Moderate Income	$48,001 - $69,000	12.5%	6.0%	1.2%	1.4%	7.2%

Source: American Community Survey, HUD Income Limits, CFPB/HMDA Dynamic National Loan-Level Dataset

Table 6.36 Results of the Indicator for McLennan County (2019)

Income Cohort	Income Range	Demand	Over(under) supply: Conventional	Over(under) supply: FHA	Over(under) supply: VA	Over(under) supply: RHS
Extremely Low-Income	$0 - $25,750	41.8%	-7.6%	-4.8%	-3.8%	-10.5%
Very Low-Income	$25,751 - $32,250	9.2%	0.5%	1.2%	1.4%	0.6%
Low-Income	$32,251 - $51,600	20.9%	6.2%	5.8%	5.7%	5.1%
Moderate Income	$51,601 - $74,175	12.9%	2.9%	1.9%	1.2%	4.4%

Source: American Community Survey, HUD Income Limits, CFPB/HMDA Dynamic National Loan-Level Dataset

Strengths of the Indicator

This indicator improves on existing indicators of purchase affordability in a variety of ways, summarized as follows:

- Rather than focusing solely on the ability of median income earners to afford the median-priced home, this indicator calculates purchase affordability across the income distribution. Moreover, the income cohorts incorporated into this indicator can be customized: users may define the income ranges of interest to the particular problem at hand.
- The home price-to-income multiplier embedded in this indicator allows the characteristics of borrowers and loans to vary: users may define the values of the mortgage interest rate, loan term, DTI and LTV ratios, and additional costs of homeownership so as to be most reflective of the particular problem at hand.

- Users may customize the indicator to measure purchase affordability for different demographic groups. For example, users interested in racial and/or ethnic disparities in purchase affordability can input the relevant income distributions into the indicator. Users may also define the income distribution to reflect different housing tenures (owner- or renter-occupied households or owner- and renter-occupied households).
- Pro6ded the income and home price data is available, the indicator can be applied to any geographic scale—from block groups to the nation.

Limitations of the Indicator

This indicator presents several limitations, summarized as follows:

- Imputing income and home price prove susceptible to errors, particularly when working with wider ranges in those income and price distributions. Without knowing the precise number of households within a particular income cohort or the precise number of homes affordable to households of a particular income cohort, the results may be incorrect, skewing the interpretation and potentially the policy implications.
- The home price-to-income multiplier reflects the *expected* maximum home price affordable to a particular income cohort. Actual home prices may de6ate substantially, subject largely to conditions in the mortgage markets. During periods of high demand for mortgage loans, lenders, facing a larger pool of applicants, will be able to choose only the most creditworthy borrowers. The home price-to-income multiplier of such borrowers will likely be slightly lower than even the expected home price of those borrowers.

- The home price-to-income multiplier assumes that borrowers and lenders maximize home price according to the borrowing constraints. In reality, although able to qualify for higher home prices, many borrowers may choose to purchase a home at a lower price than is reasonably affordable to them. Lenders may also be unwilling to originate a mortgage loan for the maximum home price for which the borrower qualifies.
- The indicator lacks the simplicity—specifically, the ease of computation and interpretation—offered by other indicators of purchase affordability.
- The indicator does not consider factors which affect purchase affordability other than the supply of homes, such as locational attributes, housing quality, and racial discrimination. In other words, the framework acts in a "black box," and assumes, ceteris paribus, that households of the same income or within the same income cohort face the same availability in housing choices.
- The data on home values published by the American Community Survey presents a significant limitation in that it reflects the homeowner's perception of his/her home value. The homeowner may under- or overstate his/her home value, albeit unintentionally. Using appraisal district data or home sales data may produce more reliable results by remo6ng the potential for measurement error (i.e., the incorrect reporting of home values by respondents to the ACS). The appraised value is derived from the sales prices of comparable properties (i.e., it is intended to reflect the price for which the home would sell on the open market), while the sales price ob6ously denotes the actual value of the home.

Reliability and Validity

Reliability reflects the consistency and reproducibility of results, while validity concerns itself with whether (and how well) the method measures that which it claims to measure. In other words, with respect to this research, validity poses the question: does the indicator actually measure purchase affordability? Generally speaking, a measure which depicts high reliability tends to indicate the measure is valid (Drost, 2011). The consistency of results across the study sites in both 2018 and 2019 reflects well on the reliability of the Losey Indicator of Purchase Affordability. To further assess reliability, I compare the maximum affordable home price (i.e., the expected home price) produced by the home price-to-income multiplier to the actual home price for each loan type and year and across the three study sites. Tables 6.37 and 6.38 depict the correlation coefficients between the actual home price and both the Median Multiple and the home price-to-income multiplier.

On average, the correlation coefficients between the actual home price and expected home price produced by the home price-to-income multiplier prove stronger than those between the actual home price and expected home price produced by the Median Multiple. For example, for conventional loans in Anderson County in 2018, the correlation between the actual home price and expected home price generated by the home price-to-income multiplier equals 73.7%, while the correlation between the actual home price and expected home price predicted by the Median Multiple equals 61.2%. Moreover, the correlation coefficient between the actual home price and expected home price predicted by the home price-to-income multiplier exceeds 50% in all but one instance, and generally exceeds 60%. However, the home price-to-income multiplier does not perform as well with respect to predicting the home price of RHS-guaranteed loans.

Overall, the generally high correlation between the actual home price and the home price-to-income multiplier suggests high reliability, boding favorably for the indicator.

Table 6.37 Correlation Coefficients between the Actual Home Price and the Median Multiple and Home Price-to-Income Multiplier in 2018

		Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Anderson County	Median Multiple	61.2%	53%	76.2%	58.2%
	Home Price-to-Income Multiplier	73.7%	57.8%	87.7%	70.3%
Austin-Round Rock MSA	Median Multiple	63.7%	54%	62.9%	48.4%
	Home Price-to-Income Multiplier	77.1%	55.8%	69.2%	51.6%
McLennan County	Median Multiple	57.7%	47%	59.5%	65.9%
	Home Price-to-Income Multiplier	68.5%	54.3%	71%	55.3%

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

Table 6.38 Correlation Coefficients between the Actual Home Price and the Median Multiple and Home Price-to-Income Multiplier in 2019

		Conventional	FHA-Insured	VA-Guaranteed	RHS-Guaranteed
Anderson County	Median Multiple	81.7%	56.4%	71.7%	55.9%
	Home Price-to-Income Multiplier	76.7%	66.3%	77%	-4.1%
Austin-Round Rock MSA	Median Multiple	63.3%	58.6%	62.7%	60.7%
	Home Price-to-Income Multiplier	76%	60.2%	71.3%	56.7%
McLennan County	Median Multiple	53.5%	55.8%	60.2%	66.9%

	Home Price-to-Income Multiplier	58.2%	63.1%	63.9%	64.9%

Source: CFPB/HMDA Dynamic National Loan-Level Dataset

To assess reliability, I also computed the results of the indicator using home sales data from the Texas Real Estate Research Center (REC) and subsequently compared them to the results obtained from data on home values from the ACS. Tables 6.39-6.44 depict the results of the indicator in each study site using REC home sales data. Values in bold indicate a reversal in the sign between the results obtained using ACS and REC data (i.e., a positive value from ACS data vs. a negative value from REC data).

Comparing the results between the two sources of data indicates that the indicator is of high reliability in McLennan County and the Austin-Round Rock MSA. However, with respect to Anderson County, the results of the indicator differ considerably when using ACS vs. REC data. For instance, with respect to the results of the indicator in 2019, the REC data depicts an *under*supply of homes affordable to Extremely Low-Income households across all four loan types, while the ACS data portrays an *over*supply of homes affordable to such households. Meanwhile, the few discrepancies e6dent in the results for McLennan County and the Austin Round-Rock MSA prove of low magnitude.

Table 6.39 Results of the Indicator in Anderson County Using REC Data (2018)

Income Cohort	Income Range	Demand	Over(under) supply: Conventional	Over(under) supply: FHA	Over(under) supply: VA	Over(under) supply: RHS
Extremely Low-Income	$0 - $25,100	37.8%	**-7.4%**	1.0%	**-0.5%**	**-10.5%**
Very Low-Income	$25,101 - $28,250	5.7%	0.8%	**0.3%**	**0.6%**	0.4%

Low-Income	$28,251 - $45,200	23.5%	3.2%	4.8%	4.3%	2.6%
Moderate Income	$45,201 - $61,755	12.8%	**7.4%**	2.6%	3.4%	**8.0%**

Source: Texas Real Estate Research Center, HUD Income Limits, CFPB/HMDA Dynamic National Loan-Level Dataset
*Values in bold indicate a change in the sign of the results between the REC and ACS data.

Table 6.40 Results of the Indicator in Anderson County Using REC Data (2019)

Income Cohort	Income Range	Demand	Over(under) supply: Conventional	Over(under) supply: FHA	Over(under) supply: VA	Over(under) supply: RHS
Extremely Low-Income	$0 - $25,750	36.9%	**-4.1%**	**-2.0%**	**-2.6%**	**-3.6%**
Very Low-Income	$25,751 - $29,350	6.2%	**0.9%**	**1.3%**	**1.2%**	**1.0%**
Low-Income	$29,351 - $46,950	23.7%	**6.3%**	**6.4%**	**6.4%**	**6.3%**
Moderate Income	$46,951 - $64,055	13.6%	**3.1%**	**2.4%**	**2.8%**	**3.0%**

Source: Texas Real Estate Research Center, HUD Income Limits, CFPB/HMDA Dynamic National Loan-Level Dataset
*Values in bold indicate a change in the sign of the results between the REC and ACS data.

Table 6.41 Results of the Indicator in the Austin-Round Rock MSA Using REC Data (2018)

Income Cohort	Income Range	Demand	Over(under) supply: Conventional	Over(under) supply: FHA	Over(under) supply: VA	Over(under) supply: RHS
Extremely Low-Income	$0 - $25,800	24.3%	-23.9%	-23.4%	-23.5%	-24.0%
Very Low-Income	$25,801 - $43,000	19.1%	-14.8%	-11.1%	-12.0%	-16.3%

Low-Income	$43,001 - $68,800	23.2%	8.5%	18.3%	16.8%	4.4%
Moderate Income	$68,801 - $98,900	16.2%	14.5%	9.8%	10.5%	15.0%

Source: Texas Real Estate Research Center, HUD Income Limits, CFPB/HMDA Dynamic National Loan-Level Dataset
*Values in bold indicate a change in the sign of the results between the REC and ACS data.

Table 6.42 Results of the Indicator in the Austin-Round Rock MSA Using REC Data (2019)

Income Cohort	Income Range	Demand	Over(under) supply: Conventional	Over(under) supply: FHA	Over(under) supply: VA	Over(under) supply: RHS
Extremely Low-Income	$0 - $28,400	25.3%	-24.8%	-24.3%	-24.4%	-24.9%
Very Low-Income	$28,401 - $47,300	19.9%	-14.6%	**-7.8%**	-10.5%	-15.9%
Low-Income	$47,301 - $75,500	23.9%	13.5%	18.2%	18.4%	8.5%
Moderate Income	$75,501 - $110,285	14.4%	14.9%	11.8%	12.3%	18.0%

Source: Texas Real Estate Research Center, HUD Income Limits, CFPB/HMDA Dynamic National Loan-Level Dataset
*Values in bold indicate a change in the sign of the results between the REC and ACS data.

Table 6.43 Results of the Indicator in McLennan County Using REC Data (2018)

Income Cohort	Income Range	Demand	Over(under) supply: Conventional	Over(under) supply: FHA	Over(under) supply: VA	Over(under) supply: RHS
Extremely Low-Income	$0 - $25,100	42.9%	-27.5%	-21.9%	-22.8%	-30.3%
Very Low-Income	$25,101 - $30,000	6.9%	**-1.1%**	0.4%	0.2%	**-2.0%**
Low-Income	$30,001 - $48,000	20.0%	6.3%	13.6%	13.2%	1.3%

Moderate Income	$48,001 - $69,000	12.5%	14.3%	9.8%	9.7%	15.8%

Source: Texas Real Estate Research Center, HUD Income Limits, CFPB/HMDA Dynamic National Loan-Level Dataset
*Values in bold indicate a change in the sign of the results between the REC and ACS data.

Table 6.44 Results of the Indicator in McLennan County Using REC Data (2019)

Income Cohort	Income Range	Demand	Over(under) supply: Conventional	Over(under) supply: FHA	Over(under) supply: VA	Over(under) supply: RHS
Extremely Low-Income	$0 - $25,750	41.8%	-29.6%	-24.8%	-25.6%	-28.1%
Very Low-Income	$25,751 - $32,250	9.2%	**-1.6%**	0.3%	0.1%	**-0.6%**
Low-Income	$32,251 - $51,600	23.5%	9.0%	14.2%	13.6%	11.9%
Moderate Income	$51,601 - $74,175	12.8%	13.0%	8.6%	9.4%	11.1%

Source: Texas Real Estate Research Center, HUD Income Limits, CFPB/HMDA Dynamic National Loan-Level Dataset
*Values in bold indicate a change in the sign of the results between the REC and ACS data.

Future research should seek the expertise of realtors, mortgage lenders, and other industry professionals to assess the validity of the indicator. Professionals in both the public and private markets should be consulted; housing planners, practitioners, and policymakers indubitably bear different perceptions of the utility and soundness of the indicator than professionals in the real estate industry. Moreover, nonprofit organizations may offer different insight.

Policy Implications

The Losey Indicator of Purchase Affordability bears several policy implications:

- It allows users to estimate the effects of changes to mortgage financing terms—the mortgage interest rate, loan term, LTV ratio, and DTI ratio, the costs of mortgage financing—for conventional mortgages, private mortgage insurance; FHA-insured mortgages, annual and upfront mortgage insurance premiums; VA-guaranteed and RHS-guaranteed mortgages, the funding fee, and the additional costs of homeownership—property taxes and insurance—on purchase affordability. It also ostensibly serves as the first indicator to differentiate purchase affordability across the four primary loan types.
- Housing planners, policymakers, and practitioners can define income cohorts of interest to them, compute the indicator, and readily identify cohorts which face an undersupply of housing. This could inform decisions related to directing housing assistance, targeting programs and initiatives, etc.
- The indicator can also measure the impact of potential or proposed policy prescriptions, such as a down payment assistance program.
- Users can compute affordability at a variety of geographic scales, including the Census tract, and compare results over time and/or across geographies.

CHAPTER VII

MODELING PURCHASE AFFORDABILITY AND NEIGHBORHOOD OPPORTUNITY

The literature well-documents the positive correlation between home price and neighborhood "opportunity"—homes of higher price tend to lie in higher-opportunity neighborhoods (Heidelberg & Eckerd, 2011; Rohe & Stewart, 1996; Thomas et al., 2014). The normative standards imposed by the federal government on the neighborhoods in which subsidized rental housing is sited initiated a long litany of literature on the relationship between subsidized rental housing and neighborhood opportunity (Acevedo-Garcia et al., 2016; DeLuca & Rosenblatt, 2017; Galster, 2019; Lens & Reina, 2016). However, as yet, no research examines the relationship between purchase affordability and neighborhood opportunity, nor compares this relationship between conventional and federally-backed mortgages or among the federally-backed mortgages themselves. Generally speaking, the positive correlation between home price and neighborhood "opportunity" dictates expectations for an inverse relationship between purchase affordability and neighborhood opportunity—that is, neighborhoods with a higher proportion of lower-priced homes are likely to be of lower-opportunity (Rohe et al., 2002).

As purchase affordability and neighborhood opportunity denote latent constructs—i.e., concepts which cannot be directly measured or observed, but rather manifest themselves through observed variables, a model which measures the interaction between the two variables must be capable of parsing latent constructs from observed variables (Savalei & Bentler, 2010). As such, this chapter uses a structural equation model—specifically, confirmatory factor analysis—to examine the relationship between purchase affordability and neighborhood opportunity within the three study sites. It describes the methodology, findings across the three study sites, and policy implications.

Background

Housing and neighborhoods indelibly shape the socioeconomic outcomes of households through both essential and easily-recognizable components of daily life—access to schools, jobs, public transportation, childcare, medical care, etc.—and more latent (but equally significant) aspects of life—wealth accumulation, social support networks, and mental and emotional well-being (Galster & Killen, 1995; Jaramillo et al., 2020; Rosenbaum, 1995; Thomas et al., 2018). Households face disparate access to these markets, institutions, and services (as well as significant variation in the quality of such variables). High-opportunity neighborhoods house the best schools, jobs, daycares, medical facilities, etc; higher-income households disproportionately inhabit such neighborhoods. Meanwhile, lower-income households are intentionally sequestered into less desirable neighborhoods, effectively ensuring reduced socioeconomic outcomes through greater exposure to negative externalities such as poverty, crime and delinquency, deleterious health effects, and psychological distress (Chetty et al., 2014; Galster, 2018; Lens, 2017). Disparate access to higher-opportunity neighborhoods exacerbates pre-existing racial and economic inequalities (Green, 2015).

Within the past several decades, the rise of the geography of opportunity as a distinct field in planning and community development has resulted in several programs and policy initiatives, largely garnered toward residents of subsidized rental housing, intended to facilitate the access of such households to high-opportunity neighborhoods (O’Regan, 2017). Examples include housing mobility programs (i.e., Gautreaux, Moving to Opportunity, the Baltimore Housing Mobility Program, etc.), HOPE VI, and President Obama's Choice Neighborhoods (Galster, 2017a). In 2015, President Obama unveiled the Affirmatively Furthering Fair Housing (AFFH) rule, which married the goals of fair housing and community development (Jennings, 2012; Mast, 2015; Silverman et al., 2017).

However, while scholars have extensively studied the relationship between recipients of subsidized rental housing and the demographic characteristics of neighborhoods, there remains a paucity of research on the relationship between homeowners and the geography of opportunity. Indeed, "There is a great need for additional research that directly assesses the impacts of home ownership on local objective opportunity structures and the perception of those structures" ((Rohe et al., 2002, p. 51). The few articles that have addressed this relationship were published prior to or in the midst of the Great Recession, which vastly altered the landscape of homeownership. Since homeownership is the single largest investment a household will make, exploring the relationship between homeownership and the structural characteristics of neighborhoods is pivotal to understand the ways in which households' financial decisions and market-engineered spaces intertwine to shape individuals' outcomes (Jones et al., 2017; McCarty et al., 2019). The need for research is also bolstered by the tremendous financial clout homeownership carries even in the aftermath of the Great Recession (and its use as a policy tool to increase household wealth): "Expanding access to homeownership remains one crucial part of overcoming wealth inequality in our country" (Jacobus & Abromowitz, 2009, p. 313).

The majority of research positions the relationship between homeownership and neighborhood characteristics in the context of a standard set of demographic predictors at the tract level, including the homeownership rate, minority population, unemployment rate, and median income (Jennings, 2012). Scholars who study this relationship across cities or counties may also incorporate the dissimilarity index. (Several studies have also considered the primary borrower constraints at the tract level—the median DTI ratio, LTV ratio, and credit score.) The existing research draws heavily from the literature on segregation; it aims to address *who* gains access to homeownership and *how* neighborhood characteristics impact the odds of origination of home purchase mortgages and other loan outcomes, such as the amount (Faber, 2018; Haupert, 2019, 2020). Additionally, much literature has been generated on the relationship between subprime mortgage lending and neighborhood characteristics. However, there is a paucity of research that assesses the relationship between homeownership and the structural characteristics of neighborhoods, including access to schools, jobs, public transportation, etc. Moreover, as yet, no research examines the interaction between purchase affordability and neighborhood opportunity.

Furthermore, there remains a policy paradox regarding the role of homeownership in facilitating access to opportunity at both the household- and neighborhood-levels. As scholars and practitioners, should we advocate for policy that advances opportunities for low-income homeownership in disadvantaged neighborhoods with the expectation that higher homeownership rates in those neighborhoods will eventually stabilize the neighborhood, bolster its opportunity, and translate into better socioeconomic outcomes for households? Or should we direct low-income homeowners toward higher-opportunity neighborhoods, leaving other low-income households to grapple with deleterious conditions in disadvantaged neighborhoods? “At the individual level, households seek to optimize their opportunities through moving to the best area possible, while in aggregate policies are designed with the expectation that ownership itself will improve neighborhoods. We encourage families to move out of the very neighborhoods that we seek to improve" (Heidelberg & Eckerd, 2011, p. 4). However, answering such questions first requires a greater understanding of the relationship between purchase affordability and opportunity.

Methodology

Through confirmatory factor analysis (CFA), a statistical technique most widely used in the social sciences, researchers hypothesize and subsequently assess the relationship between observed variables and latent construct(s). Generally, observed variables denote items in a test (or scale) and latent variables serve as the constructs which the test (or scale) measures. Guided by theory and/or empirical research, the researcher specifies the nature of the relationship between the observed and latent variables—i.e., the model—a priori, including the direction of the relationship between the latent variables (i.e., recursive vs. non-recursive) and the presence of correlated error term(s). However, provided appropriate theoretical or empirical justification, the researcher may respecify the model (i.e., add or remove observed variables or add or remove parameter constraints, including correlated error terms) to improve the fit of the model (Brown & Moore, 2012; Gallagher & Brown, 2013).

This research broadly focuses on two latent constructs: purchase affordability and neighborhood opportunity—both as independent and joint concepts. As theoretical constructs, purchase affordability and neighborhood opportunity cannot be directly measured, but may instead be quantified through observed variables. As such, this research uses CFA (specifically, a two-level measurement model) to evaluate the relationship between the observed variables and the (hypothesized) latent constructs. Figure 7.1 models the path diagram of the relationship between purchase affordability and neighborhood opportunity. The observed variables for neighborhood opportunity consist of the seven Opportunity Indexes developed by HUD: the Jobs Proximity, Transit Trips, Transportation Costs, School Proficiency, Labor Market Engagement, Low Poverty, and Environmental Health Hazards Indexes. Meanwhile, the observed variables for purchase affordability consist of the characteristics of the borrower and loan. Income, race, ethnicity, sex, age and the DTI ratio signify the former, while the property value, interest rate, presence of a high-cost loan, LTV ratio, and loan type (i.e., FHA, VA, or RHS) denote the latter. (The loan term does not vary across observations, otherwise it would be included under loan characteristics.) Table 7.1 lists the number of observations incorporated into the CFA model by the study site and year.

Figure 0.1 Path Diagram of the Relationship between Purchase Affordability and Neighborhood Opportunity

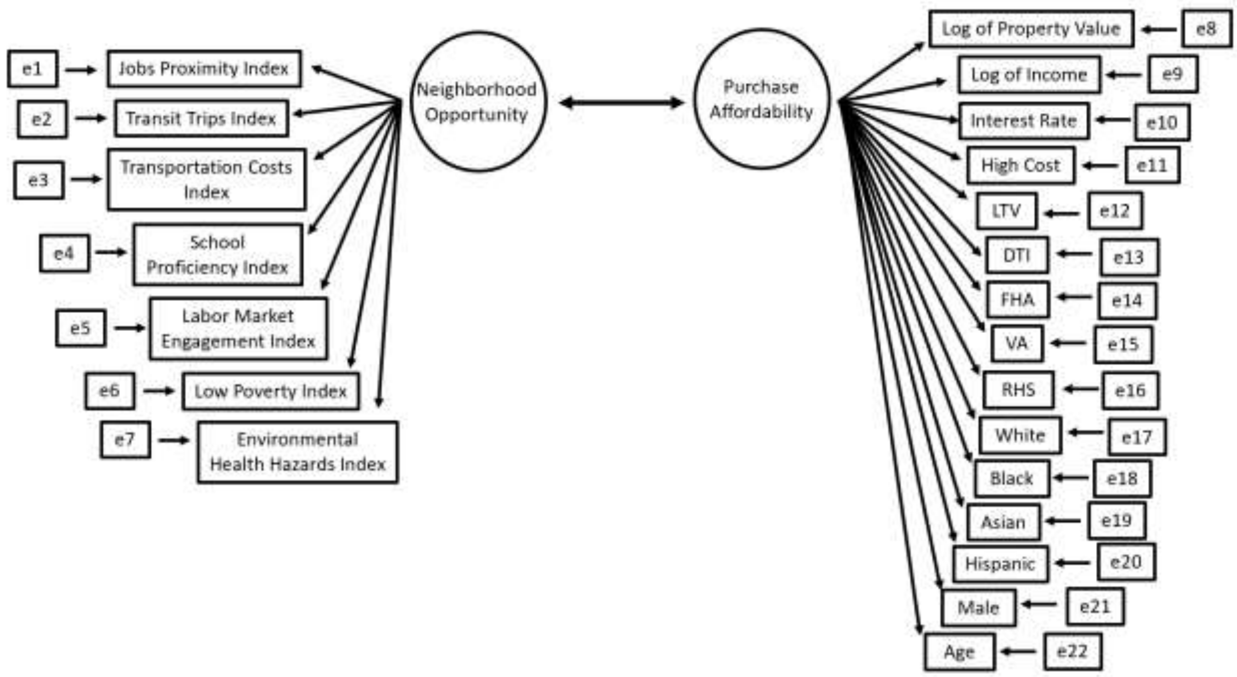


Table 7.1 The Number of Observations in Each CFA by Study Site and Year

Study Site	Year	Number of Observations
Anderson County	2018	205
	2019	470
Austin-Round Rock MSA	2018	23,970
	2019	52,226
McLennan County	2018	1,627
	2019	3,816

Source: CFPB/HMDA Dynamic National Loan-Level Dataset, HUD AFFH Dataset (AFFHT0006)

Purchase affordability and neighborhood opportunity vary considerably by geography, dictating separate CFAs for each of the three study sites. Moreover, as the CFPB/HMDA dataset reflects mortgage loan originations in 2018 and 2019, the analyses were conducted separately for each year, generating six models in total. Initially, each model was run without any correlated error terms. Researchers generally prefer to conduct an initial CFA without correlated error terms, namely to ensure appropriate statistical justification for introducing correlated error terms (otherwise, the researcher could increase the odds of overspecification) (Brown & Moore, 2012; Gallagher & Brown, 2013). After assessing the fit and modification indices for each of the three initial models, with further justification from both the literature and the methodology underlying HUD's Opportunity Indexes, I added correlations among the error terms. Tables 7.2-7.4 list the correlated error terms for each study site as well as the rationale for the inclusion of those terms. Meanwhile, Figures 7.2-7.4 depict the revised path diagrams for each study site, which include the modifications indices.

Table 7.2 Modification Indices for Anderson County

Exogeneous Variable	Correlated Error Term	Rationale
Jobs Proximity Index	Labor Market Engagement Index	Neighborhoods with strong labor market engagement—i.e., a low unemployment rate, high labor force participation rate, and high proportion of the population (25 years and older) with at least a bachelor's degree—should also house a higher concentration of jobs (Ellen et al., 2018; McDonald, 2004). Neighborhoods with a strong labor pool will prove more attractive to employers, who will be more likely to site businesses in those neighborhoods.
Low Poverty Index	Environmental Health Hazards Index	The literature bears a long litany of research documenting the disproportionately high siting of lower-income households in neighborhoods of greater exposure to environmental hazards (Kershaw et al., 2013; Yandle & Burton, 1996). One would therefore anticipate a strong positive correlation between the Low Poverty and Environmental Health Hazards Indexes.

Exogeneous Variable	Correlated Error Term	Rationale
School Proficiency Index	Transit Trips Index	School quality generally correlates significantly with the household income of its students; poorer quality schools generally serve lower-income students, whose families, on average, use public transportation more frequently.
Environmental Health Hazards Index	Transportation Costs Index	Neighborhoods with higher exposure to environmental health hazards may lie on the outskirts of town, which indicates that residents of those neighborhoods must travel farther to the center of town.
Environmental Health Hazards Index	Transit Trips Index	Neighborhoods with higher exposure to environmental health hazards tend to house lower-income households, which, on average, use public transportation more frequently.
Interest Rate	High Cost	The odds of observing a high-cost loan depend on the rate spread, which is a function of the interest rate. In other words, the odds of observing a high-cost loan indirectly relies on the interest rate.
High Cost	FHA	The propensity of high-cost loans proves considerably higher among FHA loans. (High-cost loans comprise 60.2% of FHA loans versus 28.7% of all loans in Anderson County.)
White	Black	This research separates the borrower's race into one of four categories: white, black, Asian, or other. (The CFA model only reflects the first three variables due to collinearity.) The odds of observing one of the variables directly affects the odds of observing the other variables.
White	Asian	

Figure 0.2 Path Diagram with Modification Indices for Anderson County

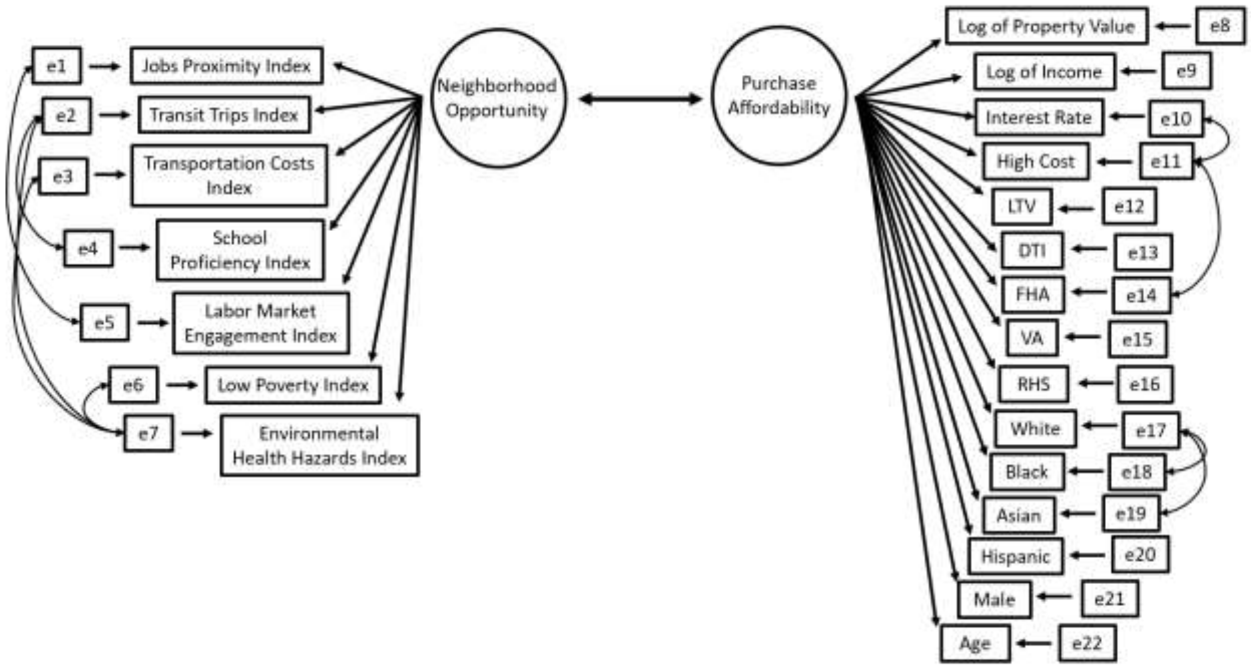


Table 7.3 Modification Indices for the Austin-Round Rock MSA

Exogeneous Variable	Correlated Error Term	Rationale
Low Poverty Index	School Proficiency Index	Poorer-performing schools generally tend to lie in higher-poverty neighborhoods. Indeed, the Low Poverty and School Proficiency Indexes bear a strong positive correlation in the Austin-Round Rock MSA (r = 0.62).
Low Poverty Index	Labor Market Engagement Index	Neighborhoods which depict a higher unemployment rate, lower labor force participation rate, and lower educational attainment

Exogeneous Variable	Correlated Error Term	Rationale
		generally portray a higher poverty rate.
School Proficiency Index	Labor Market Engagement Index	The income of neighborhoods which depict a higher unemployment rate, lower labor force participation rate, and lower educational attainment generally measures below the average income for the region. School quality correlates positively with income; lower-income neighborhoods, generally characterized by lower labor market engagement, tend to house poorer quality schools.
Log of Property Value	Log of Income	Property value and income bear a strong correlation in the Austin-Round Rock MSA (73.4%); generally, a change in one of the two variables corresponds to a similar change in the other.
Log of Property Value	DTI	The DTI ratio inherently depends on the borrower's income. As the borrower's income correlates strongly with property value, the DTI ratio indirectly depends on the property value.
Log of Income	LTV	The LTV ratio acts as a function of the property value.
Interest Rate	High Cost	The odds of observing a high-cost loan act as a function of the rate spread, which depends on the interest rate. In other words, the odds of observing a high-

Exogeneous Variable	Correlated Error Term	Rationale
		cost loan indirectly relies on the interest rate.
High Cost	FHA	The propensity of high-cost loans proves considerably higher among FHA loans. (High-cost loans comprise 38.6% of FHA loans vs 8.2% of all loans in the Austin-Round Rock MSA.)
White	Black	This research separates the borrower's race into one of four categories: white, black, Asian, or other. (The CFA model only reflects the first three variables due to collinearity.) The odds of observing one of the variables directly affects the odds of observing the other variables.
White	Asian	

Figure 0.3 Path Diagram with Modification Indices for the Austin-Round Rock MSA

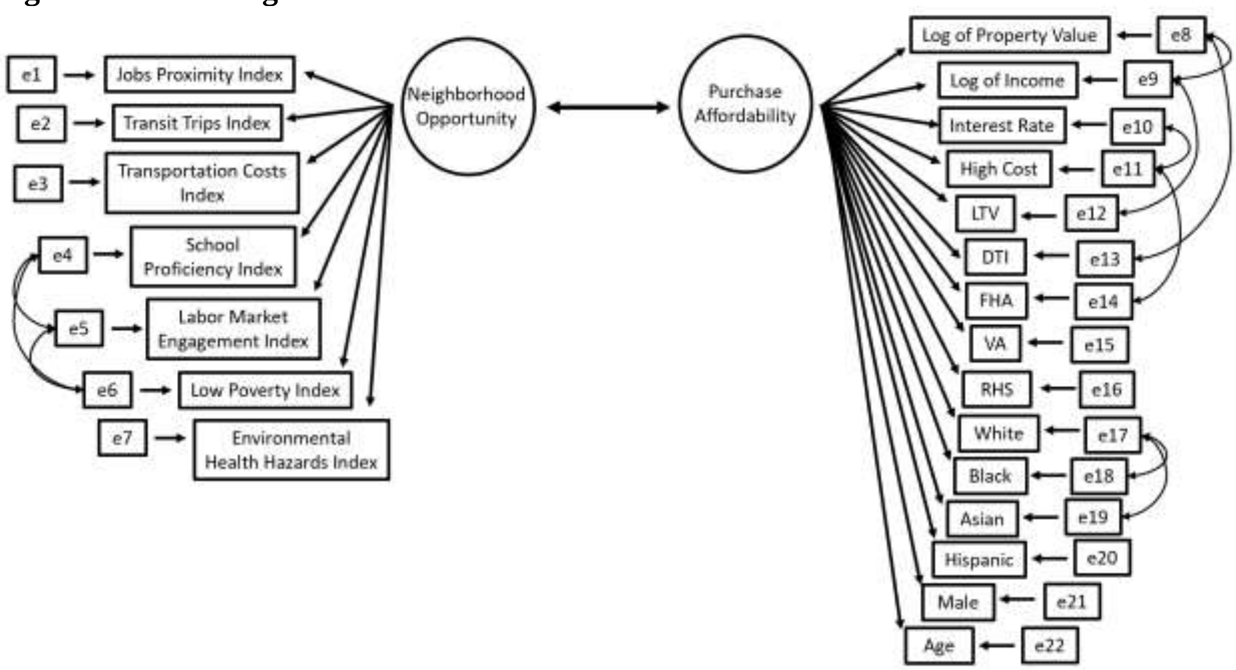


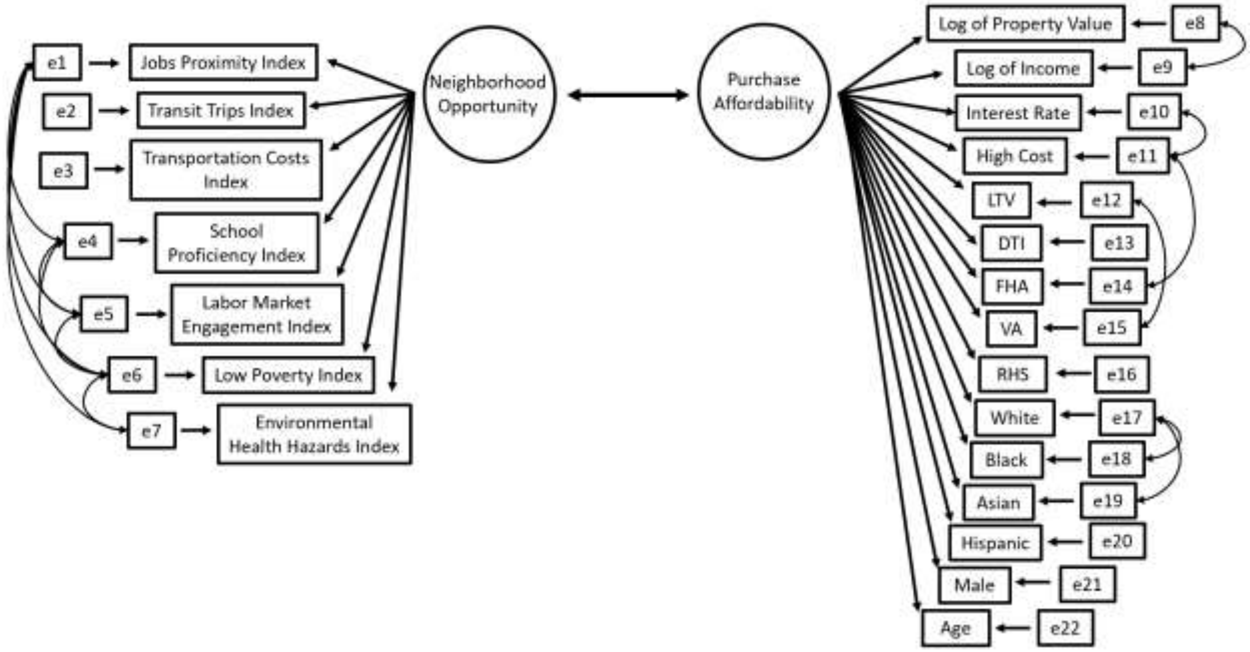
Table 7.4 Modification Indices for McLennan County

Exogeneous Variable	Correlated Error Term	Rationale
Jobs Proximity Index	Low Poverty Index	Lower poverty neighborhoods tend to house a higher concentration of jobs.
Jobs Proximity Index	School Proficiency Index	The positive correlation between school quality and jobs accessibility to the income of a neighborhood suggests an association between the two former.
Jobs Proximity Index	Labor Market Engagement Index	Theory holds that neighborhoods with strong labor market engagement—i.e., a low unemployment rate, high labor force participation rate, and high proportion of the population (25 years and older) with at least a bachelor's degree—should also witness a higher concentration of jobs. Neighborhoods with a strong labor pool will prove more attractive to employers in the decision on siting businesses.
Jobs Proximity Index	Environmental Health Hazards Index	Neighborhoods with greater jobs accessibility tend to depict lower exposure to environmental health hazards.
Low Poverty Index	School Proficiency Index	Poorer-performing schools generally tend to lie in higher-poverty neighborhoods. Indeed, the Low Poverty and School Proficiency Indexes bear a strong positive correlation

Exogeneous Variable	Correlated Error Term	Rationale
		in the Austin-Round Rock MSA (r = 0.81).
Low Poverty Index	Labor Market Engagement Index	Neighborhoods which depict a higher unemployment rate, lower labor force participation rate, and lower educational attainment generally portray a higher poverty rate.
Low Poverty Index	Environmental Health Hazards Index	The literature bears a long litany of research documenting the disproportionately high siting of lower-income households in neighborhoods of greater exposure to environmental hazards. One would therefore anticipate a strong positive correlation between the Low Poverty and Environmental Health Hazards Indexes.
School Proficiency Index	Labor Market Engagement Index	The income of neighborhoods which depict a higher unemployment rate, lower labor force participation rate, and lower educational attainment generally measures below the average income for the region. School quality correlates positively with income; lower-income neighborhoods, generally characterized by lower labor market engagement, tend to house poorer quality schools.
Log of Property Value	Log of Income	Property value and income bear a strong correlation in McLennan County (64.1%);

Exogeneous Variable	Correlated Error Term	Rationale
		generally, a change in one of the two variables corresponds to a similar change in the other.
Interest Rate	High Cost	The odds of observing a high-cost loan act as a function of the rate spread, which depends on the interest rate. In other words, the odds of observing a high-cost loan indirectly relies on the interest rate.
High Cost	FHA	The propensity of high-cost loans proves considerably higher among FHA loans. (High-cost loans comprise 55% of FHA loans vs 20.6% of all loans in McLennan County.)
LTV	VA	VA loans tend to depict high LTVs.
White	Black	This research separates the borrower’s race into one of four categories: white, black, Asian, or other. (The CFA model only reflects the first three variables due to collinearity.) The odds of observing one of the variables directly affects the odds of observing the other variables.
White	Asian	

Figure 0.4 Path Diagram with Modification Indices for McLennan County



Findings

This section presents the results of the CFA conducted for each study site; specifically, the standardized path estimates and R-squared values for each observed variable, the fit indices for each model, and the standardized covariances between the two latent constructs. As each observed variable corresponds to only one latent variable, the standardized path estimates denote the correlation coefficient between the observed and latent variables. Meanwhile, the R-squared values depict the proportion of the variance of the latent variable explained by the observed variable. The standardized covariance represents the correlation between two latent variables.

Fit indices typically reported for SEM models include the chi-square statistic, root mean square error of approximation (RMSEA), standardized root mean square residual (SRMR), and comparative fit index (CFI) (Sun, 2005). Overall, “fit” encapsulates the ability of the model to accurately reflect the underlying data. A model of good fit will reproduce the data well, as denoted by the values of the fit indices. The fit indices broadly capture differences between the predicted and observed (i.e., actual) data, with values for the predicted data computed from the structure of the hypothesized model.

The chi-square statistic evaluates the overall fit of the model and the difference between the sample and fitted covariance matrices. The threshold for the p-value of the chi-square statistics is 0.05; a model with a chi-square statistic greater than 0.05 is generally considered to be of good fit. However, the chi-square statistic proves sensitive to the number of observations (i.e., sample size). As the sample size increases, the sensitivity of the chi-square statistic also increases (i.e., a higher propensity of observing a statistically significant p-value). The RMSEA evaluates the discrepancy between the hypothesized model and the population covariance matrix. The SRMR, an absolute measure of fit, depicts the standardized difference between the residuals of the sample covariance matrix and the hypothesized model. With respect to both the RMSEA and SRMR, values less than 0.08 are generally considered to denote a good fitting model. The CFI evaluates the difference between the observed data and the hypothesized model. Values equal to or greater than 0.90 are typically considered to portray a model of good fit.

Anderson County

Tables 7.5 and 7.6 portray the standardized path estimates and R-squared values in 2018 and 2019, respectively, for the observed variables which depict neighborhood opportunity. In both models, the Transit Trips and Labor Market Engagement Indexes are not statistically significant, while the Low Poverty Index is significant at the 0.05 level. Among the seven observed variables, the Jobs Proximity and Transportation Costs Indexes appear to be most strongly correlated with neighborhood opportunity, with standardized path estimates close to 90%. The School Proficiency and Environmental Health Hazards Indexes—for which the standardized path estimates hover around 80%—also appear to be highly correlated with neighborhood opportunity. Meanwhile, the Low Poverty Index seems to be moderately correlated with neighborhood opportunity. However, the Transit Trips and Labor Market Engagement Indexes, which lack statistical significance, appear to be weakly correlated with neighborhood opportunity.

With R-squared values between approximately 70% and 80%, the Jobs Proximity, Transportation Costs, and School Proficiency Indexes explain a high fraction of the variance of neighborhood opportunity. The Environmental Health Hazards Index, with an R-squared value around 60%, also explains a high proportion of the variance of neighborhood opportunity. Meanwhile, the Transit Trips and Labor Market Engagement Indexes explain a very low proportion of the variance of neighborhood opportunity. The Low Poverty Index explains a moderate proportion of the variance of neighborhood opportunity.

Table 7.5 Latent Variable Analysis of Neighborhood Opportunity in Anderson County (2018)

Observed Variable	**Standardized Path Estimate**	**R-Squared**
Jobs Proximity Index	0.892***	79.5%
Transit Trips Index	-0.311	9.7%
Transportation Costs Index	0.894***	79.9%
School Proficiency Index	-0.846***	71.5%
Labor Market Engagement Index	-0.027	0.1%
Low Poverty Index	-0.560*	31.4%
Environmental Health Hazards Index	-0.780***	60.8%

*** p<0.001, ** p< 0.01, *p<0.05

Table 7.6 Latent Variable Analysis of Neighborhood Opportunity in Anderson County (2019)

Observed Variable	Standardized Path Estimate	R-Squared
Jobs Proximity Index	0.897***	80.4%
Transit Trips Index	-0.298	8.9%
Transportation Costs Index	0.888***	78.9%
School Proficiency Index	-0.831***	69.1%
Labor Market Engagement Index	0.077	0.6%
Low Poverty Index	-0.500*	25.0%
Environmental Health Hazards Index	-0.765***	58.6%

*** $p<0.001$, ** $p< 0.01$, *$p<0.05$

Tables 7.7 and 7.8 portray the standardized path estimates and R-squared values in 2018 and 2019, respectively, for the observed variables which represent purchase affordability. While property value and income bear a strong and moderate correlation, respectively, to purchase affordability, most observed variables depict poor correlation to purchase affordability. The LTV ratio appears moderately correlated with purchase affordability. As expected, only property value and income explain a high proportion of the variance of purchase affordability. The R-squared values for property value measure particularly high—94.3% and 77.5% in 2018 and 2019, respectively. The R-squared values for income, while smaller at 47.3% and 59.5% in 2018 and 2019, respectively, indicate moderate correlation between income and purchase affordability.

Table 7.7 Latent Variable Analysis of Purchase Affordability in Anderson County (2018)

Observed Variable	Standardized Path Estimate	R-Squared
Log of Property Value	0.971***	94.3%
Log of Income	0.688***	47.3%
Interest Rate	-0.189***	3.6%
High Cost	-0.193**	3.7%
LTV	-0.367***	13.5%
DTI	0.025	0.1%
FHA	-0.146*	2.1%
VA	0.015	0.0%
RHS	-0.220***	4.8%
White	0.135***	1.8%

Observed Variable	Standardized Path Estimate	R-Squared
Black	-0.119**	1.4%
Asian	-0.037	0.1%
Hispanic	-0.170*	2.9%
Male	-0.233***	5.4%
Age	0.105	1.1%

*** p<0.001, ** p< 0.01, *p<0.05

Table 7.8 Latent Variable Analysis of Purchase Affordability in Anderson County (2019)

Observed Variable	Standardized Path Estimate	R-Squared
Log of Property Value	0.880***	77.5%
Log of Income	0.772***	59.5%
Interest Rate	-0.102	1.0%
High Cost	-0.141***	2.0%
LTV	-0.356***	12.6%
DTI	-0.217	4.7%
FHA	-0.261***	6.8%
VA	0.091	0.8%
RHS	-0.271***	7.3%
White	0.109*	1.2%
Black	-0.135*	1.8%
Asian	0.014	0.0%
Hispanic	-0.093	0.9%
Male	0.247	6.1%
Age	0.197*	3.9%

*** p<0.001, ** p< 0.01, *p<0.05

Finally, the standardized covariances—which measure -40.4% and -41.0%—depict moderate negative correlation between purchase affordability and neighborhood opportunity (see Table 7.9). In other words, an increase in purchase affordability denotes a decrease in neighborhood opportunity (and vice versa). Tables 7.10 and 7.11 depict the fit statistics in Anderson County in 2018 and 2019, respectively. The fit statistics indicate that, despite the modifications to the overarching model, it fits the underlying data poorly. The values of the chi-square statistic render both highly statistically significant. (Indicating that we reject the null hypothesis that the model is of perfect fit.) The RMSEA for both years measure well above 0.08

(0.121 and 0.131 in 2018 and 2019, respectively). Meanwhile, the CFI falls substantially below 0.90—0.773 and 0.735 in 2018 and 2019, respectively. The SRMR proves reasonably close to 0.08 (0.096 and 0.088 in 2018 and 2019, respectively).

Table 7.9 Standardized Covariances between Purchase Affordability and Neighborhood Opportunity in Anderson County

2018	-0.404
2019	-0.410

Table 7.10 Goodness of Fit Statistics in Anderson County (2018)

Control Variable	**Value**
Chi-Square	798.221***
RMSEA	0.121
CFI	0.773
SRMR	0.096

*** p<0.001, ** p< 0.01, *p<0.05

Table 7.11 Goodness of Fit Statistics in Anderson County (2019)

Control Variable	**Value**
Chi-Square	1801.228***
RMSEA	0.131
CFI	0.735
SRMR	0.088

*** p<0.001, ** p< 0.01, *p<0.05

Austin-Round Rock MSA

Tables 7.12 and 7.13 portray the standardized path estimates and R-squared values in 2018 and 2019, respectively, for the observed variables which represent neighborhood opportunity. All but one observed variable—the School Proficiency Index—are statistically significant at the 0.001 level. Four of the observed variables—the Jobs Proximity, Transit Trips, Transportation Costs, and Environmental Health Hazards Indexes—bear a strong correlation with neighborhood opportunity (the correlation exceeds 75% across all indexes). The Low Poverty Index moderately correlates with neighborhood opportunity, while both the School Proficiency and Labor Market Engagement Indexes poorly correlate with neighborhood opportunity.

With R-squared values above 70%, the Transit Trips, Transportation Costs, and Environmental Health Hazards Indexes explain a high fraction of the variance of neighborhood opportunity. The Jobs Proximity Index, with R-squared values around 60%, also explains a high proportion of the variance of neighborhood opportunity. Meanwhile, the School Proficiency, Labor Market Engagement, and Low Poverty Indexes explain a very low proportion of the variance of neighborhood opportunity.

Table 7.12 Latent Variable Analysis of Neighborhood Opportunity in the Austin-Round Rock MSA (2018)

Observed Variable	**Standardized Path Estimate**	**R-Squared**
Jobs Proximity Index	0.773***	59.7%
Transit Trips Index	0.839***	70.5%
Transportation Costs Index	0.887***	78.7%
School Proficiency Index	-0.100	1.0%
Labor Market Engagement Index	0.216***	4.7%
Low Poverty Index	-0.333***	11.1%
Environmental Health Hazards Index	-0.931***	86.6%

*** $p<0.001$, ** $p< 0.01$, *$p<0.05$

Table 7.13 Latent Variable Analysis of Neighborhood Opportunity in the Austin-Round Rock MSA (2018)

Observed Variable	**Standardized Path Estimate**	**R-Squared**
Jobs Proximity Index	0.766***	58.6%
Transit Trips Index	0.846***	71.6%
Transportation Costs Index	0.893***	79.8%
School Proficiency Index	-0.077	0.6%
Labor Market Engagement Index	0.230***	5.3%
Low Poverty Index	-0.313***	9.8%

Environmental Health Hazards Index	-0.937***	87.9%

*** p<0.001, ** p< 0.01, *p<0.05

Tables 7.14 and 7.15 portray the standardized path estimates and R-squared values in 2018 and 2019, respectively, for the observed variables which represent purchase affordability. Five variables—property value, income, the LTV and DTI ratios, and FHA (i.e., the presence of an FHA loan)—appear strongly correlated with purchase affordability. Property value—with standardized path estimates near 0.7—bears a particularly high correlation with purchase affordability. Meanwhile, interest rate, high cost (i.e., the presence of a high-cost loan), and Hispanic (i.e., the presence of Hispanic borrower) depict moderate correlation with purchase affordability. The remaining observed variables correlate poorly with purchase affordability.

As expected, property value and income explain a fair proportion of the variance of purchase affordability—nearly one-half and one-third, respectively. The LTV and DTI ratios—with R-squared values between 30% and 40%—also explain a moderate proportion of the variance of purchase affordability. FHA explains a lower proportion of said variance (approximately one-quarter). Meanwhile, the remaining observed variables explain a low proportion of the variance of purchase affordability.

Table 7.14 Latent Variable Analysis of Purchase Affordability in the Austin-Round Rock MSA (2018)

Observed Variable	**Standardized Path Estimate**	**R-Squared**
Log of Property Value	0.692***	47.9%
Log of Income	0.569***	32.4%
Interest Rate	-0.332***	11.0%
High Cost	-0.368***	13.5%
LTV	-0.633***	40.1%
DTI	-0.564***	31.8%
FHA	-0.496***	24.6%
VA	-0.177***	3.1%
RHS	-0.125***	1.6%

Observed Variable	Standardized Path Estimate	R-Squared
White	-0.020	0.04%
Black	-0.160***	2.6%
Asian	0.155***	2.4%
Hispanic	-0.312***	9.7%
Male	0.105***	1.1%
Age	0.143***	2.1%

*** p<0.001, ** p< 0.01, *p<0.05

Table 7.15 Latent Variable Analysis of Purchase Affordability in the Austin-Round Rock MSA (2019)

Observed Variable	Standardized Path Estimate	R-Squared
Log of Property Value	0.697***	48.5%
Log of Income	0.584***	34.1%
Interest Rate	-0.266***	7.1%
High Cost	-0.334***	11.2%
LTV	-0.603***	36.3%
DTI	-0.578***	33.5%
FHA	-0.480***	23.0%
VA	-0.193***	3.7%
RHS	-0.099***	1.0%
White	-0.007	0.0%
Black	-0.169***	2.8%
Asian	0.155***	2.4%
Hispanic	-0.294***	8.7%
Male	0.105***	1.1%
Age	0.103***	1.1%

*** p<0.001, ** p< 0.01, *p<0.05

Finally, the standardized covariances—32.4% and 37.9% in 2018 and 2019, respectively—depict moderate correlation between purchase affordability and neighborhood opportunity (see Table 7.16). An increase in purchase affordability is associated with an increase in neighborhood opportunity. Tables 7.17 and 7.18 depict the fit statistics for the Austin-Round Rock MSA in 2018 and 2019, respectively. The fit statistics indicate that, with the modifications to the overarching model, it fits the underlying data fairly well. The values of the chi-square statistic render both highly statistically significant. (Indicating that we reject the null hypothesis that the model is of perfect fit.) However, observing such significance may be a byproduct of its sensitivity to the high sample size. The RMSEA for both years measures 0.08. Meanwhile, the CFI approximates 0.90—0.884 and 0.882 in 2018 and 2019, respectively. The SRMR proves fairly close to 0.08 (0.090 and 0.088 in 2018 and 2019, respectively).

Table 7.16 Standardized Covariances between Purchase Affordability and Neighborhood Opportunity in the Austin-Round Rock MSA

2018	0.324
2019	0.379

Table 7.17 Goodness of Fit Statistics for the Austin-Round Rock MSA (2018)

Control Variable	**Value**
Chi-square	30470.444 ***
RMSEA	0.080
CFI	0.884
SRMR	0.090

*** p<0.001, ** p< 0.01, *p<0.05

Table 7.18 Goodness of Fit Statistics for the Austin-Round Rock MSA (2018)

Control Variable	**Value**
Chi-square	66408.222***
RMSEA	0.080
CFI	0.882
SRMR	0.088

*** p<0.001, ** p< 0.01, *p<0.05

McLennan County

Tables 7.19 and 7.20 depict the factor loadings, or standardized path estimates, for neighborhood opportunity in McLennan County in 2018 and 2019, respectively. All seven observed variables show a significant loading on neighborhood opportunity. The Transportation

Costs Index, for which the R-squared values measure 98.8% and 99.6% in 2018 and 2019, respectively, seems the most reflective of neighborhood opportunity, followed by the Environmental Health Hazards and Transit Trips Indexes. Although still significant, the Low Poverty and Labor Market Engagement Indexes are considerably less reflective of neighborhood opportunity than the previously-mentioned four indicators. In particular, the Labor Market Engagement Index appears to poorly characterize neighborhood opportunity.

The signs of the coefficients indicate that, ceteris paribus, the School Proficiency, Labor Market Engagement, Low Poverty, and Environmental Health Hazards Indexes are negatively correlated with neighborhood opportunity. Meanwhile, the positive signs of the other observed variables suggest that, ceteris paribus, an increase in each of these variables would increase neighborhood opportunity.

Table 7.19 Latent Variable Analysis of Neighborhood Opportunity in McLennan County (2018)

Observed Variable	**Standardized Path Estimate**	**R-Squared**
Jobs Proximity Index	0.664***	44.1%
Transit Trips Index	0.713***	50.8%
Transportation Costs Index	0.994***	98.8%
School Proficiency Index	-0.674***	45.4%
Labor Market Engagement Index	-0.390***	15.2%
Low Poverty Index	-0.534***	28.5%
Environmental Health Hazards Index	-0.738***	54.5%

*** p<0.001, ** p< 0.01, *p<0.05

Table 7.20 Latent Variable Analysis of Neighborhood Opportunity in McLennan County (2019)

Observed Variable	**Standardized Path Estimate**	**R-Squared**
Jobs Proximity Index	0.655***	42.9%
Transit Trips Index	0.652***	42.4%
Transportation Costs Index	0.998***	99.6%
School Proficiency Index	-0.653***	42.7%
Labor Market Engagement Index	-0.390**	15.2%
Low Poverty Index	-0.512***	26.2%

Environmental Health Hazards Index	-0.729***	53.1%

*** p<0.001, ** p< 0.01, *p<0.05

Tables 7.21 and 7.22 portray the factor loadings for purchase affordability in McLennan County in 2018 and 2019, respectively. All variables bear significant loadings on purchase affordability. Two variables—the LTV ratio and FHA loans—depict high R-squared values of 35.8% and 31.4%, respectively. The R-squared values for the log of property value and high-cost loans—26.8% and 24.5%, respectively—indicate fairly high reflectivity of purchase affordability. However, the presence of all significant indicators, the generally low R-squared values of several of the observed variables, including the log of income, loan term, interest rate, DTI ratio, VA loans, and RHS loans, suggest poor reflectivity of the latent variable.

The signs of the coefficients indicate that, ceteris paribus, an increase in the property value or income of the borrower would diminish purchase affordability; moreover, the presence of a VA loan also decreases purchase affordability. Meanwhile, the positive signs of the other observed variables suggest that, ceteris paribus, an increase in each of these variables would increase purchase affordability.

Table 7.21 Latent Variable Analysis of Purchase Affordability in McLennan County (2018)

Observed Variable	**Standardized Path Estimate**	**R-Squared**
Log of Property Value	0.568***	32.2%
Log of Income	0.295***	8.7%
Interest Rate	-0.484***	23.4%
High Cost	-0.540***	29.1%
LTV	-0.501***	25.1%
DTI	-0.145**	2.1%
FHA	-0.531***	28.2%
VA	0.341***	11.6%
RHS	-0.095***	0.9%
White	0.079*	0.6%
Black	-0.091*	0.8%
Asian	0.017	0.0%

Hispanic	-0.284***	8.1%
Male	0.154***	2.4%
Age	0.372***	13.8%

*** p<0.001, ** p< 0.01, *p<0.05

Table 7.22 Latent Variable Analysis of Purchase Affordability in McLennan County (2019)

Observed Variable	Standardized Path Estimate	R-Squared
Log of Property Value	0.550***	30.2%
Log of Income	0.281***	7.9%
Interest Rate	-0.385***	14.8%
High Cost	-0.535***	28.6%
LTV	-0.560***	31.4%
DTI	-0.210***	4.4%
FHA	-0.589***	34.7%
VA	0.305***	9.3%
RHS	-0.076***	0.6%
White	0.132***	1.7%
Black	-0.171***	2.9%
Asian	0.050	0.2%
Hispanic	-0.218***	4.7%
Male	0.193***	3.7%
Age	0.331***	11.0%

*** p<0.001, ** p< 0.01, *p<0.05

Finally, the standardized covariances (-24.7% and -21.3% in 2018 and 2019, respectively) depict low correlation between purchase affordability and neighborhood opportunity (see Table 7.23). An increase in purchase affordability is associated with a decrease in neighborhood opportunity (and vice versa). Tables 7.24 and 7.25 depict the fit statistics for McLennan County in 2018 and 2019, respectively. The fit statistics indicate that, with the modifications to the overarching model, it fits the underlying data fairly well. The values of the chi-square statistic render both highly statistically significant. (Indicating that we reject the null hypothesis that the model is of perfect fit.) However, observing such significance may be a byproduct of its sensitivity to the high sample size. The RMSEA for both years measures 0.08.

Meanwhile, the CFI approximates 0.90—0.884 and 0.882 in 2018 and 2019, respectively. The SRMR proves fairly close to 0.08 (0.090 and 0.088 in 2018 and 2019, respectively).

Table 7.23 Standardized Covariances between Purchase Affordability and Neighborhood Opportunity in McLennan County

2018	-0.247
2019	-0.213

Table 7.24 Goodness of Fit Statistics for CFA for McLennan County (2018)

Control Variable	**Value**
Chi-square	2620.45
RMSEA	0.088
CFI	0.876
SRMR	0.095

*** p<0.001, ** p< 0.01, *p<0.05

Table 7.25 Goodness of Fit Statistics for CFA for McLennan County (2019)

Control Variable	Value
Chi-square	5215.491
RMSEA	0.082
CFI	0.878
SRMR	0.084

Policy Implications

The results of the CFA model indicate that the direction of the relationship between purchase affordability and neighborhood opportunity depends significantly on the particular geography of interest. Anderson County and McLennan County depicted the expected negative correlation; i.e., in both of those geographies, as purchase affordability increases, neighborhood opportunity decreases. However, in the Austin-Round Rock MSA, purchase affordability and neighborhood opportunity depicted a direct relationship—i.e., as purchase affordability increases, neighborhood opportunity also increases. Findings from the CFA indicate that planners, policymakers, and practitioners should avoid making generalist assumptions about the relationship between purchase affordability and neighborhood opportunity and instead seek to elucidate the association between the two within a particular geography of interest.

CHAPTER VIII

THE AFFORDABILITY-OPPORTUNITY MAPPING TOOL

Considerable contention permeates the intersection of fair housing and community development; housing affordability and neighborhood opportunity lie at the heart of this tension (Davidson, 2009; Galster, 2017a; O'Regan, 2017). The inherent tradeoff between the two lends itself to a dualistic relationship: the positive correlation between home prices and neighborhood opportunity dictates that, on average, housing affordability measures higher in lower-opportunity neighborhoods and lower in higher-opportunity neighborhoods (Acevedo-Garcia et al., 2016; Heidelberg & Eckerd, 2011; Rohe et al., 2002; Walter & Wang, 2016). Planners, policymakers, and practitioners broadly aim to facilitate both purchase affordability and neighborhood opportunity; however, as a result of the opposing nature of the two, face difficult parameters within which to achieve such an aim (Mast, 2015; Turner, 2017). Moreover, planners, policymakers, and practitioners must abide by the normative standards imposed by the federal government on the neighborhoods in which subsidized rental housing is sited, facilitating further tension between fair housing and community development scholars and activists (Imbroscio, 2016a; Silverman et al., 2017). Mounting concerns over housing affordability and rising attention—particularly at the federal level—on neighborhood opportunity thrusts this debate into the forefront (Dokko, 2018; Lung-Amam et al., 2018).

Planners, policymakers, and practitioners frequently rely on quantitative data analysis, including indexes, maps, and other indicators, to measure perceived problems, inform planning and policy decisions, direct federal, state, or local housing assistance, and/or procure funding themselves. These individuals generally embed quantitative data analysis into a broad array of planning reports, from Comprehensive Plans, which pertain to localized planning needs, to the Analysis of Impediments to Fair Housing Choice, a mandate of recipients of HUD funding (Dokko, 2018; Mast, 2015; Silvermam et al., 2013; Silverman et al., 2017). An indicator of housing affordability, the HUD standard—which stipulates that housing is unaffordable for households that spend more than 30% of income on housing costs—serves as the federal standard for housing assistance (Jewkes & Delgadillo, 2010; O'Dell et al., 2004). Meanwhile, recent federal mandates require localities and municipalities to use opportunity maps to measure neighborhood opportunity (Gourevitch, 2018; Knaap et al., 2014; Turner et al., 2020). As housing affordability and neighborhood opportunity continue to garner greater attention from planners, policymakers, and practitioners, expectations dictate the ubiquity of indicators of purchase affordability and opportunity maps will increase.

However, to meet the dual (and often mutually opposing) objective of facilitating housing affordability and neighborhood opportunity, planners, policymakers, and practitioners need a framework which concurrently measures both. This chapter unveils a new—in fact, presumably the first—method to simultaneously model purchase affordability and neighborhood opportunity: the Affordability-Opportunity Mapping Tool. It combines the Losey Indicator of Purchase Affordability with the seven HUD Opportunity Indexes to produce the Affordability-Opportunity Index, the values of which users assign to pre-specified categories and plot on a map. The Index reflects the disparity in the interaction between purchase affordability and neighborhood opportunity within a particular neighborhood (i.e., a Census tract) and the interaction between the two variables within a broad geography (i.e., a city, county, or MSA). Values close to zero indicate that the interaction between purchase affordability and neighborhood opportunity within a particular Census tract approximates its average value for the broad geography, while values further from zero indicate that the interaction between the two variables within a particular Census tract measures either higher or lower than its average value for the broad geography.

This chapter provides a detailed description of the design of the Affordability-Opportunity Mapping Tool. It also reviews the results of the Mapping Tool for the three study sites. Lastly, it discusses the strengths and limitations of the framework and its reliability and validity.

Design of the Affordability-Opportunity Mapping Tool

The Affordability-Opportunity Mapping Tool harnesses the Affordability-Opportunity Index to depict spatially the interaction between purchase affordability and neighborhood opportunity at the Census tract level. The methodology for the Affordability-Opportunity Mapping Tool closely resembles that of opportunity mapping in that it involves the computation of an underlying index (the Affordability-Opportunity Index) and subsequently assigns the values of the Index to one of three categories, which bear normative designations (akin to “low” vs. “high opportunity”) (Knaap, 2017). The key dissimilarity between the Mapping Tool and opportunity mapping centers on the interaction between purchase affordability and neighborhood opportunity with respect to the former, while the latter focuses solely on neighborhood opportunity (Knaap et al., 2014).

Empirically derived, the Affordability-Opportunity Index draws from the Losey Indicator of Purchase Affordability and the seven HUD Opportunity Indexes. Specifically, the Index incorporates the mismatch between household demand for homeownership and the corresponding supply of homes within a particular Census tract as well as within a broad geography. The Index measures the disparity in the interaction between purchase affordability and neighborhood opportunity within a particular neighborhood (i.e., a Census tract) and the interaction between the two variables within a broad geography (i.e., a city, county, or MSA). In other words, the mapping tool permits users to compare the interaction between purchase affordability and neighborhood opportunity across neighborhoods situated within a broad geography.

The Index uses publicly-available data from the U.S. Census Bureau. It harnesses a free online, interactive mapping platform, Carto, which does not require any expertise or special knowledge in GIS. Carto also allows users to click on any Census tract to see the values of the Index, as well as the standardized scores of purchase affordability and neighborhood opportunity.

Methodology for the Affordability-Opportunity Mapping Tool

This section reviews the steps involved in the computation of the Affordability-Opportunity Index. As the Index acts as a function of the Losey Indicator of Purchase Affordability and the Opportunity Indexes, the computation proves somewhat convoluted. However, it is enhanced by the ability of users to download a publicly accessible spreadsheet to calculate the results for the Losey Indicator of Purchase Affordability.

Step 1. Define the Geography(s) of Interest

The user must first specify the broad geography(s) of interest, such as a city, county, or MSA or two or more cities, counties, or MSAs. Although the Affordability-Opportunity Mapping Tool reflects the interaction between purchase affordability and neighborhood opportunity at the Census tract level, the broad geography provides a basis for the comparison of the relationship between purchase affordability and neighborhood opportunity among different neighborhoods.

Step 2. Define the Type of Mortgage Loan of Interest

As a function of the Losey Indicator of Purchase Affordability, the Affordability-Opportunity Mapping Tool can depict the relationship between purchase affordability and neighborhood opportunity for conventional, FHA-insured, VA-guaranteed, or RHS-guaranteed mortgages. However, should the user wish to model purchase affordability and neighborhood opportunity for more than one loan type, he/she will need to compute the Index separately for each loan type (and therefore create separate maps for each loan type). In other words, the Index cannot simultaneously model loan types.

Step 3. Define the Income or Price Distribution(s) of Interest

Although the Affordability-Opportunity Index can reflect purchase affordability for any given income or price distribution, unlike the Losey Indicator of Purchase Affordability, it cannot simultaneously compute purchase affordability across income or price distributions. In other words, the Affordability-Opportunity Index can only depict purchase affordability for one income or price distribution—for example, Extremely Low-Income households, homes priced between $100,000 and $150,000, etc. Should the user wish to model purchase affordability and neighborhood opportunity for more than one income or price distribution, he/she must compute the Index separately for each of those distributions (and therefore create separate maps).

Step 4. Calculate the Losey Indicator of Purchase Affordability

See Chapter 7 (“Toward an Improved Indicator of Purchase Affordability) for the methodology behind the Losey Indicator of Purchase Affordability.

Step 5. Specify the Opportunity Index(es) of Interest

Users may select from either one of the seven HUD Opportunity Indexes (i.e., the Low Poverty, School Proficiency, Jobs Proximity, Labor Market Engagement, Environmental Health Hazards, Transportation Costs, or Transit Trips Index) or the aggregate Opportunity Index, an average of the seven HUD Opportunity Indexes. Should the user wish to model purchase affordability and neighborhood opportunity for more than one Opportunity Index, he/she must compute the Index separately for each of those Indexes (and therefore create separate maps).

Step 6. Calculate the Affordability-Opportunity Index

Users must first multiply the value for purchase affordability (i.e., the percentage of homes under- or over-supplied to households within a particular income distribution) by the value for neighborhood opportunity (i.e., the value of the designated Opportunity Index) within a given Census tract.

Step 7. Categorize the Values of the Affordability-Opportunity Index

The user should designate each value of the Affordability-Opportunity Index into one of three categories: low, medium, or high (see Table 8.1).

Step 8. Map the Affordability-Opportunity Index

The last step involved in the Affordability-Opportunity Mapping Tool is to depict the results spatially (i.e., map the index). Users can use any mapping platform, but I recommend Carto as it is free, publicly-available, and interactive.

Interpretation of the Affordability-Opportunity Index

As a function of the interaction between purchase affordability and neighborhood opportunity, the interpretation of the Affordability-Opportunity Index requires a certain degree of nuance. At its core, the Index measures the disparity in the interaction between purchase affordability and neighborhood opportunity at the Census tract level and the interaction between the two variables within a broad geography (i.e., a city, county, or MSA). Within this research, the broad geography consists of the three study sites (Anderson and McLennan Counties and the Austin-Round Rock MSA).

The values for the Index fall into one of three categories: low, medium, or high, as depicted in Table 8.1. The interpretation of any given value of the Index depends heavily on the other values of the Index; the values are all relative. It is imperative to note that a high value does not necessarily indicate that the Census tract is of high purchase affordability *and* high neighborhood opportunity. Rather, it indicates that the combination of the two within that Census tract is high relative to the combination of the two within the broad geography. (The same holds true for a low value.)

Table 8.1 The Interpretation of the Affordability-Opportunity Index

Affordability-Opportunity Index	Category	Interpretation
Less than -0.6	Low	The interaction between purchase affordability and neighborhood opportunity within the Census tract

		measures below its average for the broad geography.
Greater than or equal to -0.6 and less than 0.25	Medium	The interaction between purchase affordability and neighborhood opportunity within the Census tract approximates its average for the broad geography.
Greater than 0.25	High	The interaction between purchase affordability and neighborhood opportunity within the Census tract exceeds its average for the broad geography.

Computing the Affordability-Opportunity Index: An Example

This section reviews the computation of the Affordability-Opportunity Index for Anderson County in 2019. Specifically, in this example, the Index reflects purchase affordability for Extremely Low-Income households, or those earning no more than 30% of area median income, who obtained conventional mortgage financing. This example uses the aggregate Opportunity Index (i.e., the average of the seven Opportunity Indexes) as the metric for neighborhood opportunity. Table 8.2 displays the values involved in the computation of the Affordability-Opportunity Index. The average value of purchase affordability for the broad geography (i.e., the three study sites) measures -12.8%; the average value of neighborhood opportunity, 57.9%. Meanwhile, the average value of the interaction between purchase affordability and neighborhood opportunity measures -9%. Within each Census tract, the values for purchase affordability exceed the average across the three study sites, indicating that homeownership is more affordable for Extremely Low-Income households in Anderson County than in other geographies within the study sites. Meanwhile, the values for neighborhood opportunity measure below the average across the three study sites, indicating that neighborhoods in Anderson County are of lower opportunity than other geographies within the study sites.

Table 8.2 Values Involved in the Computation of the Affordability-Opportunity Index

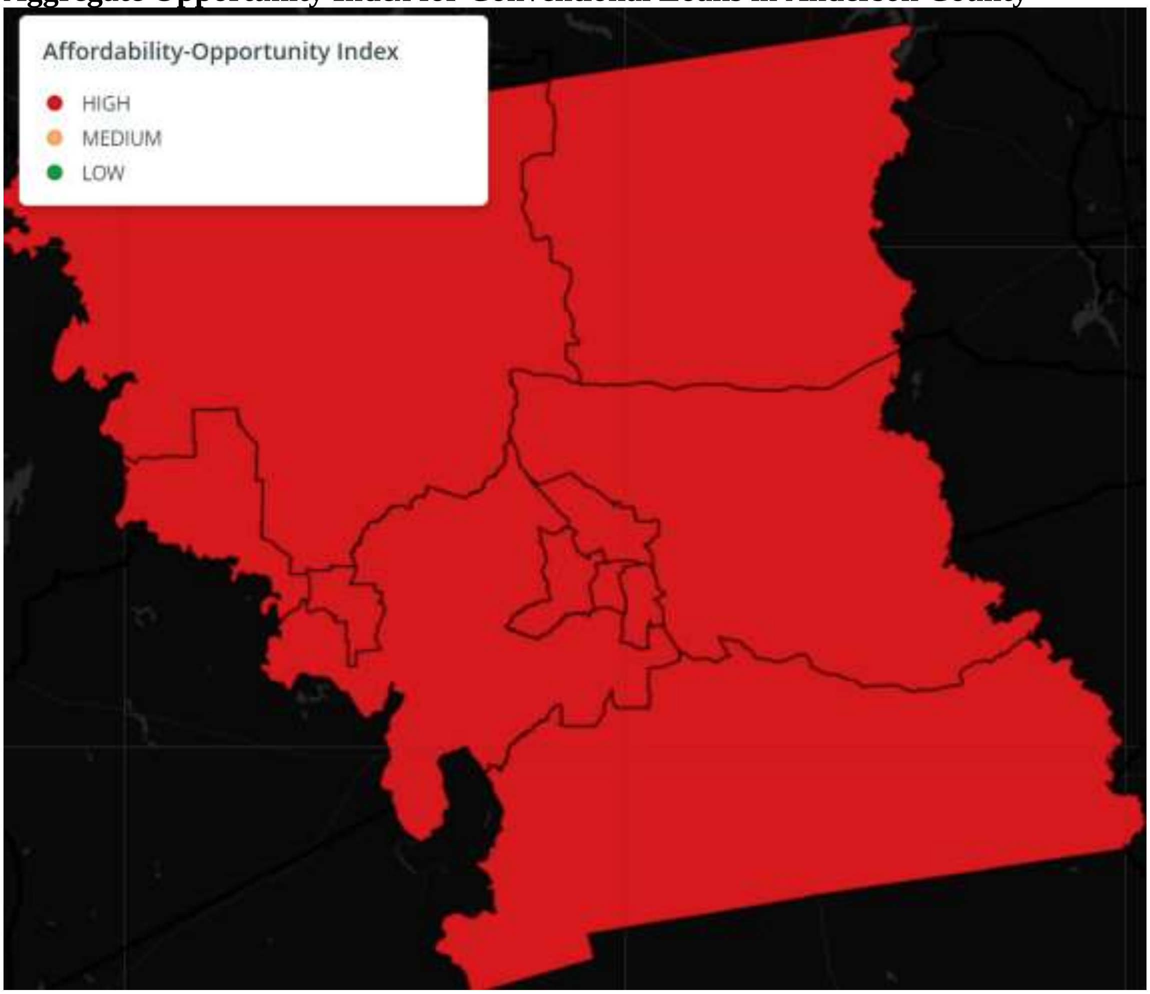
Census Tract	Purchase Affordability (Extremely Low-Income Households)	Neighborhood Opportunity (School Proficiency Index)	Interaction between Purchase Affordability and Neighborhood Opportunity	Z-Score of the Interaction between Purchase Affordability and Neighborhood Opportunity	Category
48001950100	4.5%	36.8%	1.6%	1.13	High
48001950401	45.4%	21.6%	9.8%	1.99	High
48001950402	63.1%	25.4%	16%	2.65	High
48001950500	27.3%	25.7%	7%	1.70	High
48001950600	17.0%	28.9%	4.9%	1.47	High
48001950700	38.7%	24.1%	9.3%	1.94	High
48001950800	-6.5%	39.5%	-2.6%	0.68	High
48001950901	11.1%	31.5%	3.5%	1.32	High
48001950902	6.1%	31.5%	1.9%	1.16	High
48001951000	9.9%	40.1%	4%	1.38	High
48001951100	9.8%	30.4%	3%	1.27	High

Results

This section reviews the results of the Affordability-Opportunity Mapping Tool for the three study sites in 2019. Specifically, these results reflect the interaction between the aggregate Opportunity Index and purchase affordability for Extremely Low-Income households (i.e., households earning no more than 30% of area median income). I compare the results between conventional and FHA-insured mortgage loans. Overarchingly, the results indicate clustering among tracts of similar designations (i.e., high, medium, or low).

In Anderson County, while neighborhood opportunity measures below the average across the three study sites, purchase affordability well exceeds its average across the three study sites, indicating greater access to homeownership among Extremely Low-Income households. Provided the results of the Losey Indicator of Purchase Affordability, which indicated an oversupply of homes affordable to the lowest-income cohort (Extremely Low-Income households) in 2019, the findings are perhaps unsurprising. However, the results generally suggest greater disparities between purchase affordability and neighborhood opportunity in the more populous geographies, McLennan County and the Austin-Round Rock MSA.

Figure 0.1 Map of the Interaction between Extremely Low-Income Households and the Aggregate Opportunity Index for Conventional Loans in Anderson County

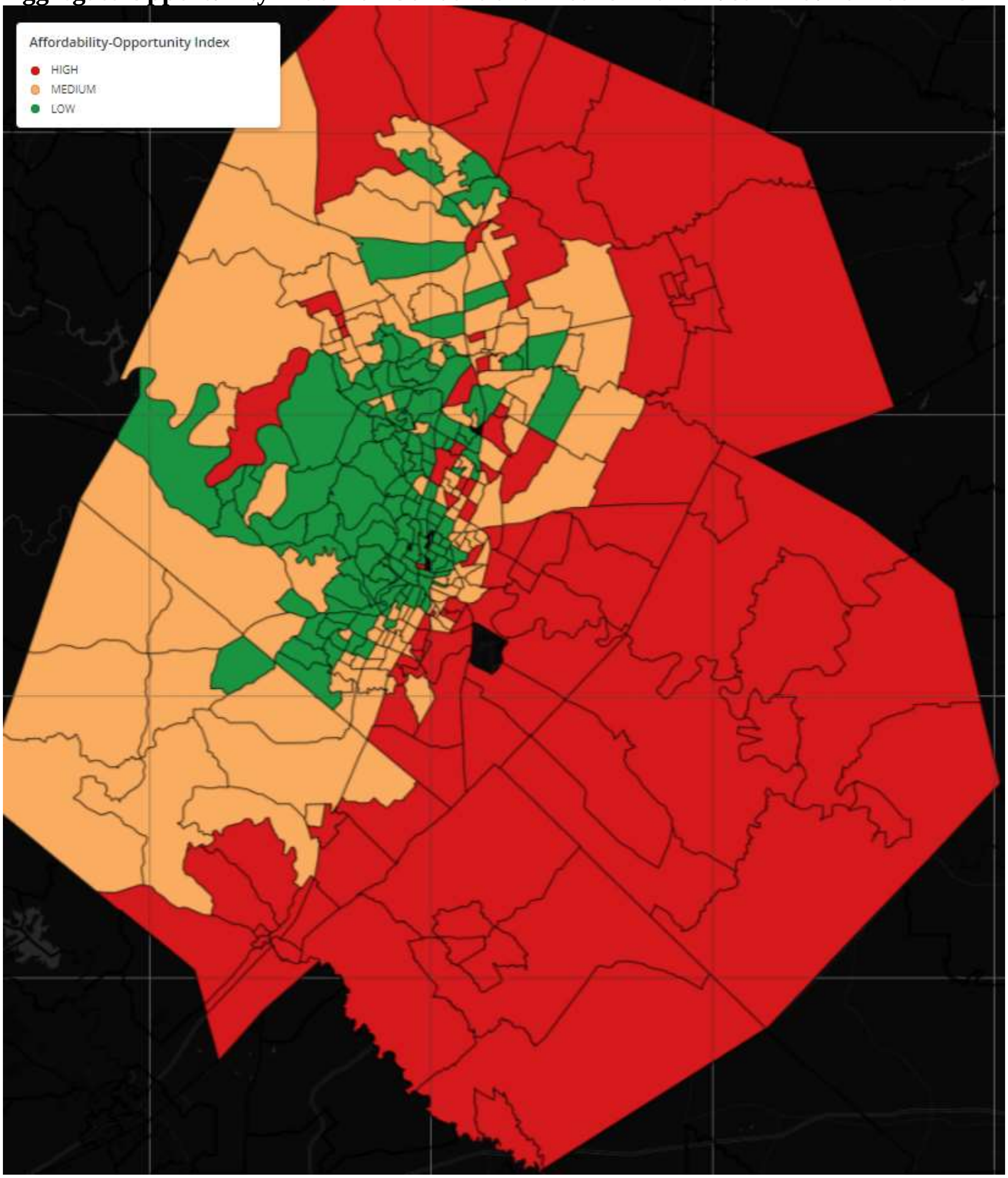


Source: American Community Survey, HUD Income Limits, CFPB/HMDA Dynamic National Loan-Level Dataset, HUD AFFH Dataset (AFFHT0006)

Figure 0.2 Map of the Interaction between Extremely Low-Income Households and the Aggregate Opportunity Index for FHA-Insured Loans in Anderson County

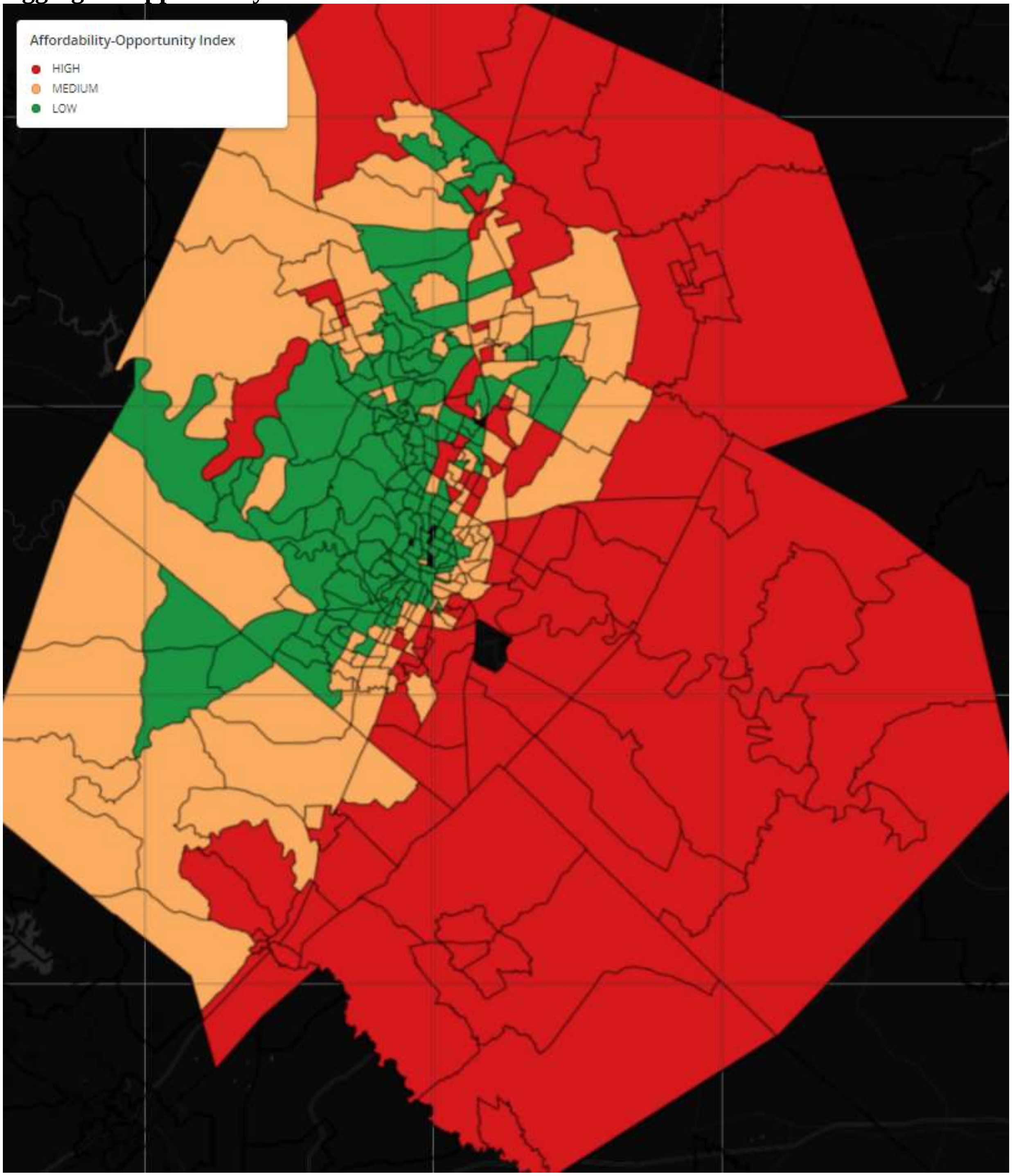
Source: American Community Survey, HUD Income Limits, CFPB/HMDA Dynamic National Loan-Level Dataset, HUD AFFH Dataset (AFFHT0006)

Figure 0.3 Map of the Interaction between Extremely Low-Income Households and the Aggregate Opportunity Index for Conventional Loans in the Austin-Round Rock MSA



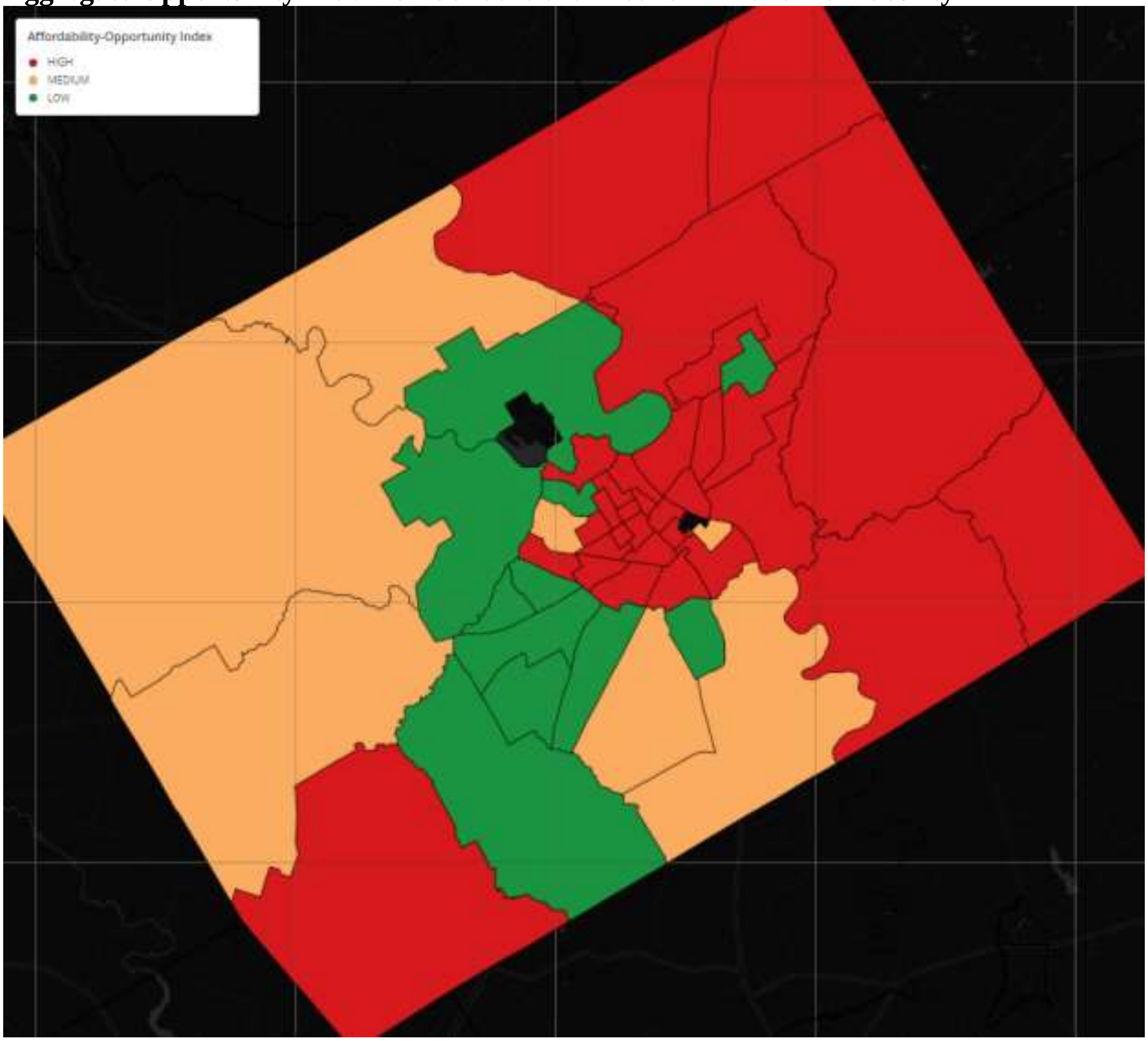
Source: American Community Survey, HUD Income Limits, CFPB/HMDA Dynamic National Loan-Level Dataset, HUD AFFH Dataset (AFFHT0006)

Figure 0.4 Map of the Interaction between Extremely Low-Income Households and the Aggregate Opportunity Index for FHA-Insured Loans in the Austin-Round Rock MSA



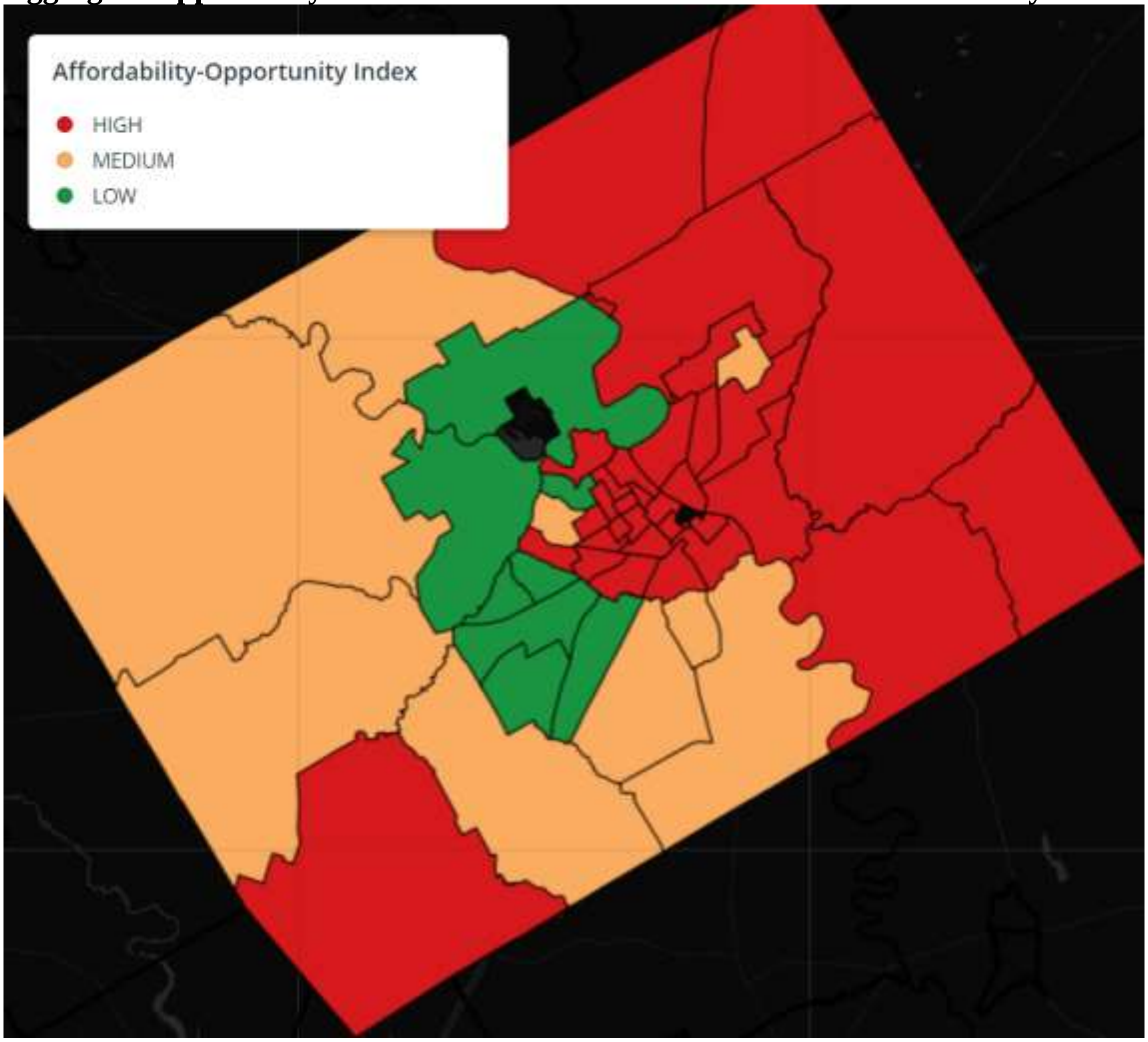
Source: American Community Survey, HUD Income Limits, CFPB/HMDA Dynamic National Loan-Level Dataset, HUD AFFH Dataset (AFFHT0006)

Figure 0.5 Map of the Interaction between Extremely Low-Income Households and the Aggregate Opportunity Index for Conventional Loans in McLennan County



Source: American Community Survey, HUD Income Limits, CFPB/HMDA Dynamic National Loan-Level Dataset, HUD AFFH Dataset (AFFHT0006)

Figure 0.6 Map of the Interaction between Extremely Low-Income Households and the Aggregate Opportunity Index for FHA-Insured Loans in McLennan County



Source: American Community Survey, HUD Income Limits, CFPB/HMDA Dynamic National Loan-Level Dataset, HUD AFFH Dataset (AFFHT0006)

Strengths of the Affordability-Opportunity Mapping Tool

The Affordability-Opportunity Mapping Tool represents presumably the first method to model the interaction between purchase affordability and neighborhood opportunity. It allows users to readily identify Census tracts in which the interaction between purchase affordability and neighborhood opportunity deviates substantially from its average value for a broad geography. It also allows users to compare the relationship between purchase affordability and neighborhood opportunity within the context of the four major types of mortgage loans: conventional, FHA-insured, VA-guaranteed, and RHS-guaranteed mortgages. The usage of publicly-available housing and income data strengthens the mapping tool.

Limitations of the Affordability-Opportunity Mapping Tool

The Affordability-Opportunity Mapping Tool presents several methodological limitations which threaten its validity or potentially diminish its utility to users. With respect to the former, the Tool relies on methods not previously subjected to rigorous validity testing, which poses perhaps the most significant threat to the validity of the Affordability-Opportunity Mapping Tool. The Tool spatially depicts the values of the Affordability-Opportunity Index, which acts as a function of the Losey Indicator of Purchase Affordability and the seven HUD Opportunity Indexes. While this research preliminarily concluded the Losey Indicator of Purchase Affordability indeed reflects purchase affordability, it should face further testing to ensure it is, in fact, a valid measure of purchase affordability. Likewise, the HUD Opportunity Indexes, recently developed, may still require further assessment.

Secondly, the complexity of the interpretation of the Affordability-Opportunity Mapping Tool may obfuscate its application by individuals who lack a sufficient grasp of purchase affordability and neighborhood opportunity. Although the designated categories (and accompanying description of the meaning of each category) should assist users in the application and interpretation of the Tool, it requires a greater degree of nuance among users. For example, the category “high” does not simply indicate the Census tract is of high affordability *and* high opportunity. Rather, it indicates that the value for the interaction between purchase affordability and neighborhood opportunity exceeds the average value for the broad geography.

Thirdly, the Index embedded in the Tool cannot currently model the interaction between purchase affordability and neighborhood opportunity across more than one home price or income distribution and Opportunity Index. Users must compute the Index separately for each home price or income distribution and Opportunity Index. For example, a user who wishes to quantify the relationship between Extremely Low-Income households, school proficiency, and environmental health hazards must compute two separate indexes, the first of which would adopt Extremely Low-Income households as the criterion for purchase affordability and school proficiency as the criterion for neighborhood opportunity, and the second of which would use Extremely Low-Income households as the measure of purchase affordability and environmental health hazards as the measure of neighborhood opportunity. Meanwhile, a user seeking to quantify the relationship between Extremely Low-Income households, Low-Income households, School Proficiency, and Environmental Health Hazards must compute four separate Affordability-Opportunity Indexes: 1) Extremely Low-Income households and the School Proficiency Index, 2) Extremely Low-Income households and the Environmental Health Hazards Index, 3) Low-Income households and the School Proficiency Index, and 4) Low-Income households and the Environmental Health Hazards Index.

Lastly, similar to opportunity mapping, the Affordability-Opportunity Mapping Tool uses arbitrary categories to distinguish between neighborhoods (i.e., Census tracts). Such a phenomenon imposes normative standards on the values of purchase affordability and neighborhood opportunity: it encourages users to negatively perceive neighborhoods in which the values for purchase affordability and/or neighborhood opportunity measure below the average value(s) for the broader region. Moreover, the signs of each variable complicate the interpretation of the Affordability-Opportunity Index. For example, within the “High” category, purchase affordability and neighborhood opportunity could present two positive values, two negative values, a positive and negative value, or a negative and positive value.

Reliability and Validity

Assessing the reliability and validity of the Affordability-Opportunity Mapping Tool poses several challenges. As a function of the Losey Indicator of Purchase Affordability and the seven HUD Opportunity Indexes, the reliability and validity of the Mapping Tool directly depend on the reliability and validity of those two indicators. Although preliminary assessments indicate high reliability and validity of the Losey Indicator of Purchase Affordability for the two more populous study sites (McLennan County and the Austin-Round Rock MSA), it does not perform as well for Anderson County. This may diminish the reliability and validity of the Affordability-Opportunity Mapping Tool in Anderson County. Regardless, further assessments of reliability and validity should be conducted before reaching more conclusive results (as explained in Chapter 7).

Moreover, as the first known measure of purchase affordability and neighborhood opportunity, future research should focus on producing results across a variety of geographies to assess the reliability and validity of the Mapping Tool. This research computed the results for only three geographies (i.e., the study sites); increasing the number of observations will allow researchers to draw more definitive findings. Generating the results across a diverse array of geographies should also assist in validating the values of the thresholds defined for the three categories (i.e., high, medium, and low).

Policy Implications

The Affordability-Opportunity Mapping Tool bears several policy implications:

- Federal housing policy largely predicates the promulgation of purchase affordability (via the federally-backed mortgages) on the notion that renters who attain homeownership move into higher-opportunity neighborhoods and that homeownership correlates positively with neighborhood opportunity (i.e., the tenet that homeowners make better neighbors and build better neighborhoods). The Mapping Tool provides the first quantitative measure of the interaction between purchase affordability and neighborhood opportunity, potentially allowing planners, policymakers, and practitioners to assess the normative standards on which homeownership is founded.
- It allows users to identify differences among the loan types in the interaction between purchase affordability and neighborhood opportunity. It also permits users to elucidate these differences across the income distribution or specific income cohorts.
- As the Affordability-Opportunity Index embedded in the mapping tool partially acts as a function of the Losey Indicator of Purchase Affordability, planners, policymakers, and practitioners can use the mapping tool to anticipate how changes in purchase affordability across the loan types will affect the interaction between purchase affordability and neighborhood opportunity.

CHAPTER IX

CONCLUSIONS

Homeownership remains the primary mechanism by which low-income and minority households build wealth (Boehm & Schlottmann, 2008; Herbert et al., 2013; Wainer & Zabel, 2020). The Survey of Consumer Finances reported 37.2%, 53.8%, and 64.6% of families in the less than 20th percentile of income cohort, 20-39.9th percentile of income cohort, and 40-59.9th percentile of income cohort, respectively, owned a primary residence in 2019. Meanwhile, the survey revealed the vast majority of minority families owned a primary residence in 2019: 45% of non-Hispanic Black or African American households, 84.5% of Hispanic or Latino households, and 81.1% of all other minorities. These figures exceed the proportion of such households that held traditional financial assets, including bonds, stocks, and retirement accounts (*Federal Reserve Board - Survey of Consumer Finances (SCF)*, n.d.).

Federally-backed mortgages—nearly one-century in the making—continue to represent the primary mechanism by which the federal government facilitates homeownership, particularly for low-income, minority, and first-time buyers—populations which traditionally experience greater difficulty in qualifying for conventional mortgage financing (Baeck & DeVaney, 2003; Fishback et al., 2001; Jones, 2018; Jones et al., 2017; Pennington-Cross & Nichols, 2000). CFPB/HMDA data indicated the three most prominent types of loans, FHA-insured, VA-guaranteed, and RHS-guaranteed mortgages, comprised over one-third of all home purchase mortgage originations in the U.S. in 2019 (*HMDA Data Publication*, n.d.). Much of the rationale for the government's vast involvement in the U.S. mortgage markets rests on the notion that homeownership—the preferred housing tenure—bears significant financial, social, health, and community benefits. Planners, policymakers, and practitioners largely promulgate homeownership based on the notion that homeowners not only make better neighbors, but also better neighborhoods (Bhutta, 2012; Carliner, 1998; Rohe et al., 2002; Rohe & Stewart, 1996).

However, the well-established positive correlation between home prices and neighborhood "opportunity" challenges such a notion (Heidelberg & Eckerd, 2011; Rohe et al., 2002; Thomas et al., 2018). Expectations dictate, then, that purchase affordability and neighborhood opportunity also bear an inverse relationship—neighborhoods with a higher proportion of affordable homes are more likely to be lower-opportunity than neighborhoods with fewer affordable homes. In other words, federal housing policy predicates the promulgation of purchase affordability on a significant fallacy: merely attaining homeownership does not necessarily signify that 1) the neighborhood opportunity of that household is "high" or 2) the neighborhood opportunity of that household even improves (Goetz, 2017; Heidelberg & Eckerd, 2011). It is vital for planners, policymakers, and practitioners to deconstruct this urban myth and flesh out the nuance in the relationship between purchase affordability and neighborhood opportunity.

Summary of Findings

The vast majority of households in the U.S rely on mortgage financing to purchase a home—86% in 2020 (Oppler, 2020). Borrowing constraints—of which the DTI ratio, LTV ratio, and credit score rank as the most prevalent—play a significant role in determining both a household's access to mortgage financing and the maximum home price affordable to a particular household (Acolin, Bricker, et al., 2016; Follain, 1990b; Linneman & Wachter, 1989).

Households of lower income, wealth, and/or credit—especially low-income and minority households—generally face greater difficultly in qualifying for conventional mortgage financing (Baeck & DeVaney, 2003; Pennington-Cross & Nichols, 2000). However, by adjusting (i.e., lowering) the borrowing constraints, federally-backed mortgages enhance purchase affordability, thereby enabling historically underserved households to attain homeownership (Jones, 2018). But such mortgages also lead to significant disparities in the maximum home price affordable to borrowers: the price of homes purchased with federally-backed mortgages tends to measure below that of homes financed with conventional loans, translating into disparities in homeowners' wealth-building potential. In other words, disparities in the income, wealth, and credit among borrowers of different loan types lead to disparities in the maximum home price for which those borrowers may qualify.

Losey Indicator of Purchase Affordability

The Losey Indicator of Purchase Affordability consistently indicated that in the two urban study sites—Austin-Round Rock MSA and McLennan County, in both 2018 and 2019, regardless of loan type, demand significantly outpaced the supply of homes affordable to the lowest-income renters. This finding indicates that homeownership is largely out of reach for Extremely Low-Income households, which earn 30% or less of area median income. However, in Anderson County—the rural study site—purchase affordability actually proved the highest for the lowest-income cohort, largely the result of the high supply of lower-priced homes throughout the county. Overarchingly, as the home price-to-income multiplier increases, the proportion of homes affordable to lower-income cohorts also increases, reducing supply constraints particularly for Very Low-Income households (those earning up to 50% of area median income). Reducing the borrowing constraints enhances purchase affordability, particularly for lower-income households, by increasing the supply of homes affordable to them.

Modeling Purchase Affordability and Neighborhood Opportunity

The results of the CFA model indicate that the direction of the relationship between purchase affordability and neighborhood opportunity depends significantly on the particular geography of interest. Anderson County and McLennan County depicted the expected negative correlation; i.e., in both of those geographies, as purchase affordability increases, neighborhood opportunity decreases. However, in the Austin-Round Rock MSA, purchase affordability and neighborhood opportunity depicted a direct relationship—i.e., as purchase affordability increases, neighborhood opportunity also increases. Findings from the CFA indicate that planners, policymakers, and practitioners should avoid making generalist assumptions about the relationship between purchase affordability and neighborhood opportunity and instead seek to elucidate the association between the two within a particular geography of interest.

Affordability-Opportunity Mapping Tool

Overarchingly, the results indicate the lack of a systematic pattern. In Anderson County, while neighborhood opportunity measures below the average across the three study sites, purchase affordability well exceeds its average across the three study sites, indicating greater access to homeownership among Extremely Low-Income households. Provided the results of the Losey Indicator of Purchase Affordability, which indicated an oversupply of homes affordable to the lowest-income cohort (Extremely Low-Income households) in 2019, the findings are perhaps unsurprising. However, the results generally suggest greater disparities between purchase affordability and neighborhood opportunity in the more populous geographies, McLennan County and the Austin-Round Rock MSA.

Policy Implications

Facilitating housing affordability and neighborhood opportunity concurrently comprises a key objective of planners, policymakers, and practitioners, a result of 1) the perceived benefits of homeownership on households and neighborhoods and 2) the perceived benefits of high-opportunity neighborhoods on inhabitants (Turner, 2017). However, the inherent dichotomy between the two particularly complicates such an objective (Galster, 2019; O'Regan, 2017). To meet the dual (and often mutually opposing) objective of facilitating both housing affordability and neighborhood opportunity, planners, policymakers, and practitioners need a framework which measures both simultaneously.

Planners, policymakers, and practitioners frequently rely on quantitative data analysis, such as indexes, maps, and other indicators, to measure the presence and magnitude of perceived problems, inform planning and policy decisions, direct federal, state, or local housing assistance (or procure funding), and compare problems across geographies or over time (Dokko, 2018). For instance, the HUD standard—which stipulates that housing is unaffordable for households that spend more than 30% of income on housing costs—serves as the federal standard for housing assistance. Meanwhile, recent federal mandates require localities and municipalities to use opportunity maps to measure neighborhood opportunity. Such analysis proves a prominent feature of planning reports, which generally guide short- and/or long-term planning decisions.

The prevalence of purchase affordability and neighborhood opportunity as planning and policy concerns dictates that the usage of these methods will likely increase over the near-term.

The two new methods proposed in this research—the Losey Indicator of Purchase Affordability and the Affordability-Opportunity Index present several policy implications. The Losey Indicator of Purchase Affordability denotes the first measure of purchase affordability that allows to estimate the effects of changes to mortgage financing terms—the mortgage interest rate, loan term, LTV ratio, and DTI ratio, the costs of mortgage financing—for conventional mortgages, private mortgage insurance; FHA-insured mortgages, annual and upfront mortgage insurance premiums; VA-guaranteed and RHS-guaranteed mortgages, the funding fee, and the additional costs of homeownership—property taxes and insurance—on purchase affordability. It also ostensibly serves as the first indicator to differentiate purchase affordability across the loan types. Moreover, the indicator allows housing planners, policymakers, and practitioners to define income cohorts of interest to them, compute the indicator, and readily identify cohorts which face an undersupply of housing. This could inform decisions related to directing housing assistance, targeting programs and initiatives, etc. The indicator computes affordability separately for conventional, FHA-insured, VA-guaranteed, and RHS-guaranteed mortgages, which permits users to elucidate the magnitude of potential disparities in affordability across loan types, as well as the implications on the borrowers who seek such mortgages.

Federal housing policy largely predicates the promulgation of purchase affordability (via the federally-backed mortgages) on the notion that renters who attain homeownership move into higher-opportunity neighborhoods and that homeownership correlates positively with neighborhood opportunity (i.e., the tenet that homeowners make better neighbors and build better neighborhoods). The Mapping Tool provides the first quantitative measure of the interaction between purchase affordability and neighborhood opportunity, potentially allowing planners, policymakers, and practitioners to assess the normative standards on which homeownership is founded.

The Mapping Tool allows users to identify differences among the loan types in the interaction between purchase affordability and neighborhood opportunity and to elucidate these differences across the income distribution or specific income cohorts. Moreover, as the Affordability-Opportunity Index embedded in the mapping tool partially acts as a function of the Losey Indicator of Purchase Affordability, planners, policymakers, and practitioners can use the mapping tool to anticipate how changes in purchase affordability across the loan types will affect the interaction between purchase affordability and neighborhood opportunity. In other words, users can assess whether, for example, increasing purchase affordability within a particular Census tract would enable households to gain access to higher-opportunity neighborhoods.

Future Research

Much of the barrier to understanding the interaction between purchase affordability and neighborhood opportunity stems from the gap in the literature and lack of tools available to planners, policymakers, and practitioners to measure the relationship. Although this research proposes two new methods, one of which measures purchase affordability and the other of which models the interaction between purchase affordability and neighborhood opportunity, future research should continue to focus on developing methods that accurately reflect such a relationship and prove easy to use and interpret. The findings of this research—as well as its methodological limitations—render several recommendations for future research.

Firstly, future research should continue to test the reliability and validity of the two new methods proposed in this dissertation (i.e., the Losey Indicator of Purchase Affordability and the Affordability-Opportunity Mapping Tool). The results for the two methods should be produced across a diverse array of geographies. Moreover, the Losey Indicator of Purchase Affordability should be estimated for a variety of income cohorts. Lastly, should the two new methods indeed prove robust, it is nevertheless imperative to understand the utility of both to planners, policymakers, and practitioners, particularly those involved in the capacities of housing and community development. The methods should be assessed by planning and policy professionals across a variety of geographies with a diverse array of housing needs.

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