Is Affordable Housing Moving Mobile? Analyzing the Impact of COVID-19 on Demand for Manufactured Housing

By

Jair Coleridge Soman Alleyne

Charles Becker, Faculty Advisor

Michelle Connolly, Faculty Advisor

Duke University

Durham, North Carolina

2022

Honors Thesis submitted in partial fulfillment of the requirements for Graduation with Distinction in Economics in Trinity College of Duke University

Acknowledgments

I would like to thank Professor Charles Becker for his guidance throughout this journey. His knowledge of and enthusiasm for manufactured housing were invaluable to me during this arduous but exciting process. I would also like to thank Professor Michelle Connolly for all her help during the research and write-up process. She constantly inspired new avenues for analysis and challenged me to further develop my economic intuition. Next, I would like to thank my Honors Seminar classmates for their thoughtful comments and my friends for their constant support throughout my research. Finally, I would like to thank my parents, from whom my interest in economics comes, for supporting and guiding me throughout my whole life. I could not have written this paper alone.

Abstract

As demand for affordable housing continues to increase in America, manufactured homes provide a private solution to this problem. Research has shown that manufactured home prices are largely dependent on the price of local housing substitutes as well as other geographic hedonic factors. This paper looks at the impact of Covid-19 on the manufactured housing market to determine the effects that economic shocks have on the demand for manufactured housing. Conditional on wanting to buy a house, we use a logistic model to examine the probability that an individual purchases a manufactured home and whether this probability increases at times of high unemployment and economic uncertainty. Due to the nature of our data, although the impact of Covid as a disease is difficult to measure, we do find decreased income and increased unemployment to be a factor increasing the likelihood of purchasing a manufactured home. We also find that in 2020, demand for manufactured housing increased significantly compared to the years prior.

JEL classification: R2, R21, I32

Keywords: Manufactured Housing, Covid-19, Hedonic Analysis, Housing Loans

Contents

1 Introduction

Manufactured housing communities (MHCs), also referred to as mobile home or trailer parks, provide a low-cost and relatively high-quality solution to the United States' lack of affordable housing options. Unlike government subsidized affordable housing or low-income apartments for rent, manufactured housing is unique in that, in most cases, ownership is split between two parties. The dual ownership structure is one in which the tenant owns the housing unit, i.e., the physical home structure, while the park owner possesses the land beneath where the unit is placed. This model is compared to other types of housing that exhibit either owner-occupancy or pure tenant-renting systems (Becker and Garcia Lemus, 2019).[1] Approximately 6.1 percent of all housing units in the USA are designated manufactured housing, and this figure jumps to 15.7 percent when looking at just rural America.[2] Over 22 million individuals live in manufactured housing. With a median annual household income of just \$30,000, the average residents are well below the national average and fall in the bottom 25$^{\text{th}}$ percentile of US household incomes.[3] Despite the large population, MHCs are generally home to a largely removed and politically inactive community. Overall, little empirical research has been done examining the characteristics of MHCs throughout the United States.

This paper will aim to provide a comprehensive analysis on the impact of COVID-19 on the demand for manufactured housing (MH) in America. Between May and October 2020, the number of Americans living in poverty grew by approximately eight million (Parolin et al., 2020).[4] With millions sent into poverty because of the pandemic, mobile homes serve as one of the most affordable private options for low-income housing for Americans living

[1] Becker Garcia Lemus (2019) p. 1

[2] See table 'Percent Of Housing Units That Are Mobile Homes' at https://www.census.gov/acs/www/data/data-tables-and-tools/geographic-comparison-tables/

[3] See https://www.manufacturedhousing.org/wp-content/uploads/2021/05/2021-MHI-Quick-Facts-updated-05-2021.pdf

[4] Parolin et al. (2020) p. 5

in rural and suburban areas. Using data on MH loan information, I aim to offer further insight into whether demand for this low-income housing option changed due to changes in market conditions spawned by the Covid-19 Pandemic.

There are main two scenarios in particular that this paper wishes to examine. The first hypothesis is that the increase in poverty and job loss and or the desire to move away from urban areas caused by the pandemic has created a spike in the demand for low-income housing in America, resulting in increased demand for mobile homes. An alternate hypothesis is that the pandemic had no measurable impact on the demand for MH. Kuk et al. (2021) link the pandemic to decreases in apartment rents in minority neighborhoods in metropolitan cities. This is likely due to the decreased demand to live in congested urban areas during the pandemic as many sought to escape to more peri-urban or rural areas. Controlling for economic market conditions and various determinants of mobile home pricing, it should be possible to quantify the impact of Covid on the overall demand for manufactured housing.

Using a dataset on Covid-19 incidence rates from USA Facts in conjunction with unemployment data from the US Bureau of Labor Statistics, this paper seeks to analyze the sensitivity of the manufactured housing market in various states to changes brought out by the pandemic, as well as isolate the impact of Covid-19 on the manufactured housing market. By measuring how hard a given region was affected by the pandemic, it allows us to control for the necessary determinants and differences in market conditions between different states, thus helping to isolate the impact of the Covid-19.

An essential focus of this paper revolves around the inherent immobility of mobile homes. In contrast to common preconceptions, manufactured housing – often interchangeably termed "mobile homes" or "trailers" – arguably lacks mobility as it costs anywhere from \$1,000 to \$20,000 to relocate a unit to a new park or area.[5] The cost to move a "mo-

[5] See https://www.mymove.com/moving/guides/move-mobile-home-cost/

bile home" to a new park also increases proportionally as the unit depreciates and external features are added to the unit. Unlike site-built housing in which the owner owns the land, manufactured homes are merely structures and thus depreciate over time as would any other form of personal property such as a boat or car. Therefore, the moment a manufactured home is placed on land, the cost relative to the value of moving starts to increase. Manufactured homes also tend to be relatively cheap, and so it becomes even more impractical for a tenant to relocate their home unit once it has been placed on a park lot as relocation costs relative to the value of the home are high. As a result, the park owners hold significant leverage over their tenants that only increases over time. Therefore, in times of above-average economic insecurity, such as in a pandemic, low-income renters of land may be less responsive to rent hikes as they cannot afford to move, as well as face higher rates and likelihoods of eviction. Additionally, previously middle-class individuals who fall into the low-income category may also wish to consume cheaper housing. Coupled with the unique effects of the pandemic, they may be prompted into leaving denser areas for manufactured housing outside urban centers.

This paper hopes to provide insight into a largely unresearched market, one that is being discussed more and more in the media as the affordable housing crisis in America continues to worsen. Over the past few years, there has been a visible uptick in the interest in mobile homes within mass media. Usually, these stories center on a mobile home park that gets bought by a corporate investment firm, where residents are faced with unfair austerity measures, suspension of park amenities, poor park upkeep, arbitrary rent hikes, or even forced eviction if the park gets shut down and the land is to be used for some other purpose. However, there has been little to no actual empirical research supporting these claims, despite the widespread news coverage on the topic. Therefore, for a future paper, it would be of great interest to explore the claim that large firms are buying up inefficiently run parks across the US and hiking up rent prices, further exacerbating financial pressure on an already generally homogeneous low-income community.

Community-owned housing has become a new solution to this problem where residents band together to attempt to buy the park themselves. However, due to many of these individuals being low-income and liquidity-constrained, they are often unable to come up with the necessary funds, only qualify for high-interest loans, and may lack the necessary managerial skills needed to run a park. Without the need to pay shareholders or worry about meeting necessary returns on investments, however, it could be that resident-owned communities (ROC) are less responsive to changes in market conditions, and thus rents, given a crash in the economy, might fluctuate less than in corporate-run parks. In future work, one may look to see whether this hypothesis is true by mapping individual rental data and looking at the type of land ownership to see if there are any differences that emerge between individual owners of land versus co-op owners of land. However, that is beyond the scope of this paper, and we only address a narrow part of this issue.

2 Literature Review

According to the US Census Bureau's American Housing Survey, 6.2% of all total housing units were manufactured homes in 2019.[6] Prior research has found that manufactured housing provides a low-cost yet relatively high-quality alternative, as measured by neighborhood characteristics and structural housing dimensions, when compared to rental housing and apartments (Boehm and Schlottman, 2004).

Looking to establish whether the Covid-19 Pandemic affected demand for manufactured homes, it is helpful to look at MHCs and establish an understanding of the elasticity of MHC lot rents in response to changes in market conditions. Hughes (2013) investigates how

[6] See the 2019 table 'Selected Housing Characteristics' at https://www.census.gov/acs/www/data/data-tables-and-tools/data-profiles/2019/

condominium prices are affected by apartment rents, single-family housing prices, and the housing price index using linear regression analysis. Becker and Garcia Lemus (2019) builds on Hughes (2013) by focusing specifically on the causal relationship between movements in MHC lot rental rates and local housing market conditions. They find that in nearly all cases, MHC rents are heavily influenced by apartment rents as well as moderately affected by single-family-unit dwelling costs. Kuk et al., (2021) analyzes the market for rental housing in the 49 largest metropolitan areas in the United States and finds that local spread of COVID-19 was followed by reduced median and mean rent for apartment rentals.[7] Specifically, they find that in the period from March – July 2020 rents fell for listings in primarily Black, Latino, and diverse neighborhoods. Listings in majority White neighborhoods, often more suburban and spacious, experienced rent increases during this time. Of course, the geographical focus of the mobile home communities focused on in this paper is not centered in densely populated metropolitan cities, so there are many different economic drivers and determinants of rent between urban rental units and mobile homes. However, Kuk et al., (2021) still serves as meaningful literature by highlighting some of the effects of Covid-19 on the rental housing market. With research suggesting mobile home community rents are influenced by changes in apartment rents and that apartment rents were affected by the pandemic, it stands to reason there should be some measurable impact on MHC rents and therefore MH demand by the Covid-19 Pandemic, and this paper seeks to quantify that impact.

Although research is scarce, empirical analysis into the determinants of MHC lot rents has been researched and documented in Becker and Garcia Lemus (2019), which uses a general method of moments 3SLS model to control for endogeneity by instrumenting for nearby apartment rents, owner-occupied home values, unit characteristics, and nearby amenities to determine the responsiveness of mobile home park lot rents in the Great Plains and

[7] Kuk et al., (2021) p. 3

Rocky Mountain States to changes in market conditions of nearby similar housing types. As mentioned before, they find evidence that local substitutable housing options do play an important factor in determining lot rents for MHC.

Becker and Rickert (2018) focuses on North Carolina and looks at the impact of zoning on MHC lot rents as well as more conventional hedonic regressions measuring the effect of characteristics like park amenities, local amenities, distance to highways, and unit quality on lot rents. As many mobile homeowners are low-income, they contribute very little in property and income taxes and use more public goods than they contribute. As a result, many municipalities will zone them out, disallowing parks in certain areas. Becker and Rickert (2018) find a strong negative and significant relationship between zoning and park rents, where areas without zoning and low barriers to entry were correlated with lower rents. They also provide key insights into the high variation of mobile home characteristics depending on rural versus urban settings, showing that because the environments are so different, in order to find meaningful results, the geographical setting of mobile homes in any empirical analysis should be controlled for— or different regions should be analyzed separately. The paper suggests that little information can be gathered by comparing mobile homes in urban areas to ones in rural locales as the determinants vary significantly and can even work in opposite directions depending on the region type. Therefore, analysis at the aggregate or state level without controlling for urbanicity yields highly misleading results—an idea further echoed by Becker and Garcia Lemus (2019).

3 Theoretical Framework

3.1 Dual Ownership Household's Utility from Manufactured Housing

For the following model, we examine the utility function of a household that purchases a manufactured home. The goal of this paper is to examine the demand for manufactured housing. To do so, one cannot look at the MH market in a vacuum. Due to the underlying connections between these different housing markets, any analysis done on the MH market ought to be done in comparison with substitutable housing options.

The underlying model builds off Becker and Yea (2015) to explain the demand for manufactured housing.[8] The theoretical household of interest seeks to maximize the following utility function:

$$U = (h, l, x) \tag{1}$$

Here, U represents the household's utility, which is a function of: $h = (h_1, ..., h_n)$, a vector of housing attributes, including the unit age, and whether unit is single wide, double wide, new, or used; $l = (l_1, ..., l_n)$ is vector of land and location attributes that include land encumberment, systemic amenities, or location-specific amenities; x = expenditure on private goods that are not housing-related.

We have already established that many residents of manufactured housing are low-income and liquidity-constrained, which is why the model is based on current annual income. The household maximizes utility subject to the following budget constraint:

$$I = x + m(h, i) + T + r(c, T, I^a, l, h_k, p^a, p^s) + c + d \tag{2}$$

I_i = household's current annual income, $m(h, i)$ = manufactured housing unit price

[8] Becker and Yea (2015) p. 8-9

function (annual housing structure cost), i = interest rate, T = household's expenditure on commuting and traveling to work and other amenities (changes based on distance to CBD/jobs, stores, schools), $r(c, T, I^a, l, m, p^a, p^s)$= hedonic park lot rents as a pricing function of park and land attributes, c = cost of transporting and placing MH on site, I^a = average annual income of locale, d = annual debt payments paid by household (includes housing-related and non-housing loans), p^a = annual payments (i.e. rent) for nearby low-income apartments, and p^s = annual payments (i.e. mortgage) for nearby single-family-unit site-built homes.

We can break down the budget constraint into two key pricing functions:

1. $m(h, i)$ **: Price Function of Manufactured Housing Unit**

   It is important to understand that m(h,i) represents the theoretical hedonic function used to price just the structure itself of the manufactured home. As a result, the only factors that need to be looked at in determining its value are the physical home attributes, h, and the interest rate, i, incurred if the household takes out a loan to finance the house.

2. $r(\ldots)$ **: Pricing Function of Park Lot Rents**

   $r(c, T, I^a, l, h_k, p^a, p^s)$ is our rent pricing function representing the cost of land attributes that will be demanded by the household and considered by the park owner when determining lot rents. If the park owner had to purchase the house from the manufacturer, they would then need to pay c to transport it and place it onto their land, which would factor into the rent that they decide to charge the tenant. But, if the household owns the land, they will not pay any rent. However, if they have to move the purchased MH to their own land —i.e. if they did not purchase a plot of land with the home already on it— the household will have to pay c. When considering the value of c in these two contexts, one can imagine that in a park, the c is being spread over all past and future tenants of a home when factored into rent prices. For an individual who owns their land, however, c is a one-time, larger payment that the individual will have to make to move the home to their desired location.

T, the cost of commuting and reaching amenities, also factors into the rent as a form of convenience tax. Given a homogeneous population with similar tastes and preferences, their vicinity to locations and amenities of interest, l, would increase demand and therefore rent as well. If the household owns their own land, they will still pay T in the form of commuting costs (time, gas, bus fare, etc.). I^a, average annual income of the locale, is included as it directly reflects the rent expected tenants would be willing and able to pay. Given the innate scarcity of land, if a certain location is highly desirable, higher-income individuals will be more willing and able to pay more for that land leading to higher rents. Less affluent households, unable to pay, will live in less desirable areas at a lower annual cost.

h_k comes from the vector $h(h_1, \ldots, h_n)$ and represents the size of the MH. It captures a minor but necessary addition as the size of the house would influence the minimum area of land needed to house the unit. The more land needed to lay the house, the higher the rent will be. p^a,p^s represent two important additions relative to Becker and Yea, (2015) whose understanding is crucial to the focus of this paper. As mentioned previously in the Literature Review, Becker and Garcia Lemus, (2019) finds that manufactured home lot rents are highly responsive to local apartment rents and moderately responsive to single-family housing prices. The intuitive underlying economic principle behind this is due to the cross elasticity of demand for low-income housing options. Although far from perfect substitutes, these remain three important forms of potential low-income affordable housing, and thus for many individuals, demand for these products can overlap and thus influence each other.

3.2 Household Demographics and Tastes and Preferences

Within a given park, both the housing units and residents tend to be fairly homogenous. In the Tiebout model, people reveal the strength of their taste for some publicly provided goods through their choice of jurisdiction in which to live. Based on individuals' respective tastes and preferences subject to their budget constraints, households will settle in a location that fits their needs. This paper utilizes loan data to look at the change in the likelihood of purchasing a manufactured home over time. Thus the method for our analysis centers around estimating demand by focusing on the housing purchase decision. We build off the Equation 1 aggregate demand function laid out Becker and Garcia Lemus (2019) as we estimate the model for an individual's demand for manufactured housing. This results in the following reduced equation that measures the demand for manufactured housing, D_i^{MH}, as a function of various hedonic characteristics at a given time and location, $Z_{ijt}(\dots)$.

$$D_i^{MH} = Z_{ijt}(P^H = m(h,i), P^L(l,\dots), P^C(p^a,p^s), H^a = h, Q^l = l, I_i, X_i, i_i) \tag{3}$$

P^H represents the price of the actual structure of the home; P^L represents the price of the land where the structure will be placed; P^C represents a vector containing the pricing of competing housing options; H^a are the housing characteristics; Q^l represents the location-specific amenities; I_i represents the individual's income; X_i is a vector with individual's demographic characteristics such as age and race; i_i is the interest rate on the loan for the home if it is being financed.

Looking at the MH market throughout the country, although not as diverse as other housing markets, the manufactured home community is still by no means monolithic. Historically, MH owners tend to live in rural or peri-urban areas, be older, and have lower incomes and net worth than site-built homeowners. For example, these may be households whose kids have grown up and moved out, are living off a lower retirement income, and demand less space than they might have during an earlier part of their life. Additionally, we see in Schneider et al., (2021) that young adults are also overrepresented within the MH market when compared to site-built owners, perhaps due to the nature of having less income when they are just starting out in their careers.[9] They show that borrowers 24 years old or younger and borrowers 55 and over are overrepresented in manufactured housing when compared to site-built borrowers.[10] While the older retired individuals may look at manufactured housing as a permanent location as they downsize their life, the younger individual might not expect to live in the unit for a long time and therefore may view it as a temporary form of housing.

These distinctions are important in that different households will have different demand elasticities and will thus have different sensitivities with respect to changes within the market. Those who view MH as a temporary form of housing may be more sensitive to changes in lot or nearby apartment rents than an older retired household. Households demand different quantities and values of housing which in turn determine the type of housing they choose. Age and racial demographics will also play a role in the type of ownership a household chooses and how they acquire it. A young single household may be more likely to choose a smaller, lower quality unit as they view it as temporary housing while the older household may opt to spend more to get a higher quality larger living space. For example, children can be thought of as space-intensive durables. Given the typically smaller size of manufactured homes compared to site-built homes, it makes sense

[9]Schneider et al., (2021)

[10]See Figure 10: Age Of Borrowers Of Site-Built And Manufactured Housing Originations from Schneider et al., (2021)

that for middle-aged-households with families, Schneider, (2021) observes less demand for MH compared to demand for conventional site-built housing.[11]

When analyzing the financing of manufactured homes, it is important to understand the difference between real and personal property. Real property is **immovable**. Real property includes the land, everything that is permanently attached to it, and the rights that come with ownership of the land. It is often, but not always, financed through a mortgage loan which is backed by the value of both the land and the structure. Personal property, on the other hand, is **movable**. Conditional on an already largely low-income population, young individuals and minorities are likely to be more credit constrained and thus may choose to buy the home as personal property, using cash, or through chattel loans at higher interest rates that are shorter term. Chattel loans refer to loans used to finance personal property. They are backed solely by the value of the structure being purchased. We see in Schneider et al., (2021) that minority borrowers make up larger shares of chattel loan borrowers than among MH mortgage loan borrowers or among site-built loan borrowers. In fact, Black and African American borrowers are the only racial group that is underrepresented in manufactured housing lending overall compared to site-built, but over-represented in chattel lending compared to site-built. Older, White, retired individuals are also seen to be more likely to finance the home as real property, by taking out a MH mortgage.[12]

3.3 Economic Shocks on the Demand for Manufactured Housing

Typically, in a recession, we can observe the lowering of house values, increases in unemployment, changes in rent, households getting behind on rent and mortgage payments, and thus an increase in foreclosure rates.[13] However, when evaluating the effect of an

[11] See Figure 10: Age Of Borrowers Of Site-Built And Manufactured Housing Originations from Schneider et al., (2021)

[12] See Figure 9: Ethnicity And Race Of Borrowers Of Site-Built And Manufactured Housing Originations (Percent) from Schneider et al., (2021)

[13] Famiglietti et al., (2020) p.52

economic shock on the housing industry, it is important to consider the type of shock as all will have inherent differences. For example, the Covid-19 Pandemic, the focus of this paper, resulted in a much different economic landscape with respect to housing compared to the 2008 housing crisis. Specifically, the 2008 recession was created by way of a housing crisis while Covid was a disease-driven shutdown of the economy. Owners and renters of manufactured homes were also more likely than residents of other housing types to work in industries that suffered significant job losses during the pandemic. To be more precise, 35 percent of MH owners work in the five industries that have lost the most jobs during the crisis (food and accommodation, retail, construction, entertainment, and other services), compared with 24 percent of site-built homeowners.[14] One key difference in outcomes between the two is an individual's access to credit post crises. After 2008, it became effectively impossible for low-income individuals to get a mortgage loan. However, since the 2020 Covid pandemic was not driven by a housing problem, coupled with the Fed's timely intervention, rates dropped to historic lows comparatively, and many more Americans had access to liquidity.[15]

As this paper is focusing on the impact that the pandemic has had on the demand for MH, let us consider the theoretical changes that a pandemic-driven recession would have on the housing market. Suppose you have groups of urban homeowners B_o^u, urban renters B_r^u , suburban/rural homeowners B_o^s, and suburban/rural renters B_r^s with housing consumption utilities U_o^u, U_r^u, U_o^s, and U_r^u, respectively. For this example, utilities will be functions solely consisting of the monetary benefits and costs of housing. Of course, there are other factors that would go into utility such as expected health outcomes and tastes and preferences, but we will ignore those for the sake of simplicity.

Let us use a highly simplified version of Equation 2 to show an individual's budget

[14] Choi and Goodman, (2020)

[15] Scott, (2021)
See Federal Funds Effective Rate (FEDFUNDS) graph at: https://fred.stlouisfed.org/series/FEDFUNDS

constraint:

$$I = x + m(\dots) + T + r(\dots) + d \tag{4}$$

Given a Covid-like recession, both renters and owners will suffer from joblessness and increased unemployment —albeit to different degrees. The homeowner group will uniquely also incur changes in property value. With a highly contagious disease spreading throughout the nation, demand for houses and apartments in congested urban areas will drop, resulting in decreased property values and rents while demand for housing in more suburban and rural areas will increase as homeowners look to escape the pandemic, driving up home values and rents. Home-owning households in these now more desirable areas may still lose their jobs and suffer financially, but they may benefit from the increased value to their home and low-interest rates, perhaps taking out a home equity loan, resulting in an ambiguous effect on their budget constraint. Thus, for suburban homeowners, the effect on their utility U_o^s is ambiguous. Home-owning households in urban areas will lose from lower income and lower home value; therefore, U_o^u will fall. Urban renters will gain from lower rents but will also suffer financially from the pandemic, so the change in U_r^u is ambiguous. Suburban/rural renters will lose due to increased rents and decreased income indicating a decrease in U_r^s.

To summarize, given a pandemic like recession, we expect:

Urban Homeowners will lose: $U_o^u \downarrow$

Urban Renters is ambiguous: $U_r^u \uparrow\downarrow$

Suburban/Rural Homeowners is ambiguous: $U_o^s \uparrow\downarrow$

Suburban/Rural Renters will lose: $U_r^s \downarrow$

Although this paper does not focus on or conduct utility analysis, the theoretical impact on various households' housing consumption utilities allows us to more accurately theorize the future actions of individuals who demand housing.

Next, let's focus on those from the losing households and renters who are low-income. Due to a tightening of their budget constraint, these groups may be pushed to consume cheaper and lower quantities of housing as they are priced out of their current consumption bundles. Empirical evidence has shown that MH lot rents are highly sensitive to nearby apartment rents and moderately sensitive to site-built costs, and so we may see a case where these suburban and rural apartment renters may choose to consume an increased level of manufactured housing. Across the board, however, due to falling incomes and the desire to leave urban areas, manufactured housing represents an affordable alternative housing option for these low-income individuals as well.

Finally, the change in demand for manufactured housing will also depend on the type of good that it represents. If MHs may act as a normal good, (i.e. like conventional housing), then as income increases, quantity demanded goes up and vice-versa. However, MHs may act as an inferior good whose demand would increase as unemployment rises and incomes fall. Based on our results, we find that an increase in income lowers the probability of purchasing a MH, suggesting they are indeed inferior goods (See Table 11). However, further empirical testing beyond the scope of this paper is needed to provide a more accurate answer to this question.

4 Empirical Framework

4.1 Probability of Manufactured Home Purchase

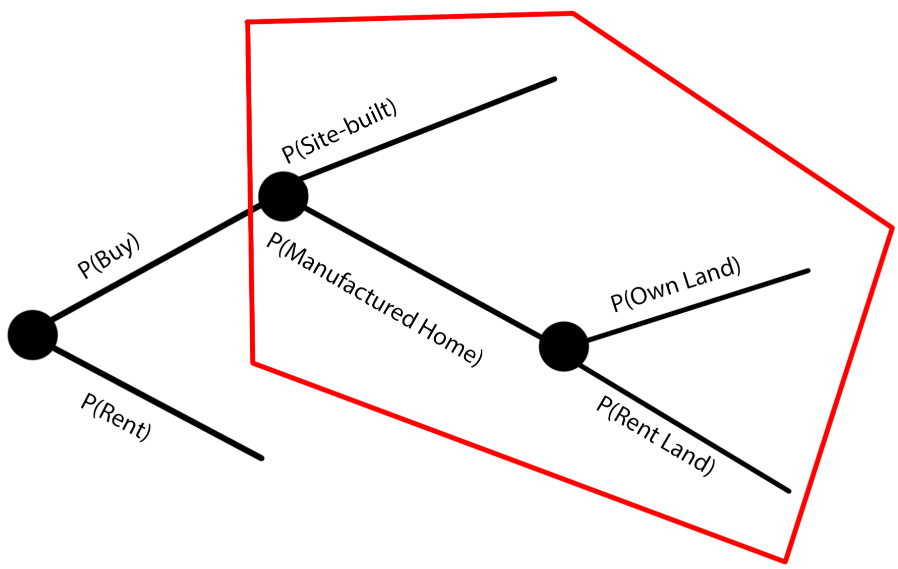
The primary dataset we use comes from the Home Mortgage Disclosure Act (HMDA) dataset published by the Consumer Financial Protection Bureau (CFPB).[16] Using HMDA

[16]See Dynamic National Loan-Level Dataset for 2017 – 2020 at https://ffiec.cfpb.gov/data-publication/dynamic-national-loan-level-dataset

individual loan-level data, this paper capitalizes on the addition of two new MH-specific variables to estimate the demand for manufactured housing (See: Section 5.1 Summary Stats Background). A complete description of the dataset, as well as its limitations, are discussed in the Data section (Section 4.2). With the goal of determining the effect Covid-19 has had on the demand for manufactured housing, we estimate the probability of an individual purchasing a manufactured home.

First, we seek to enter the mindset of an individual who needs to find new housing. Figure 1 illustrates the tree of possible outcomes for the individual.

Figure 1: Decision Tree of Individual Purchasing A Manufactured Home (Conditional on Wanting to Buy)



We assume that, given there is a demand for a new form of housing, an individual will either buy a home or rent an apartment. If they choose to buy, they can either purchase a traditional site-built home or manufactured home. Then, if they decide to purchase a manufactured home, they can either place it on land which they own or buy one in a park where they will pay rent on the land. Note that for simplification, we do not include the ability to rent a site-built home. Though of course, this option exists in reality, due to the nature of our data, we can only begin our research at the second node (outlined in red), looking at an individual's choices conditional on them buying a house.

First, this paper seeks to quantify the probability of the first possible outcome: The probability of purchasing a manufactured home relative to a site-built home. Thus, we use a logistic regression to estimate the following equation:

$$P_{ijt}^{MH} = \beta_0 + \beta_1 MH_{ijt} + \beta_2 I_{ijt} + \beta_3 R_{ijt} + \beta_4 Covid_{ij} + \beta_5 D_{2019} + \beta_6 D_{2020} + \beta_7 C_{ijt} + \beta_8 G_{ij} + \beta_9 FMR_{ijt} + \beta_{10} GXFMR_{jt} + \beta_{11} UR_{jt} + \beta_{12} Debt_{ijt} + \beta_{13} A_{ij} + \beta_{14} Sex_{ij} \varepsilon \quad (5)$$

where P^{MH}_{ijt} = probability that one purchases a manufactured house, MH_{ijt} = dummy for if an individual applies for a loan for a manufactured house, I_{ijt}= real income of individual (in thousands), R_{ijt} = race/ethnicity of borrower, G_{ij}= Urbanicity index for census tract, $Covid_{ij}$= County Covid-19 Infection Rate (EOY 2020), D_{2019} = dummy for year 2019, D_{2020}= dummy for year 2020, C_{ijt} = cost of substitutable site-built homes (in thousands), FMR_{ijt}= monthly rental cost of substitutable apartments, UR_{jt}= county level unemployment rate, $Debt_{ijt}$= average real debt holdings, A_{ij}= age group of borrower, and Sex_{ij}= sex of borrower.

As this paper is focusing on the impact of the pandemic on individuals' home purchasing outcomes, we include various key independent variables to help us address our research question. $Covid_{ij}$ gives us an idea of how hard the pandemic hit a given area. In a county with high rates of Covid, we would expect a greater increase in job loss, decrease in income, and an increased desire to escape from urban areas to more peri-urban locales. This rate is calculated by taking the total number of positive cases in each county by end of year 2020 and dividing it by each county's total population. UR_{jt} similarly is important as counties with higher rates of unemployment contain populations suffering from greater financial pressures, and thus may demand more low-income housing options. The unemployment rate helps paint a picture of the overall economic climate. As we only look at individuals who are buying a home, it is unlikely that many —if any— of the people in our dataset are actually unemployed. In our dataset, debt levels are provided in the form of a debt to income ratio range for each individual. Our $Debt_{ijt}$ variable is calculated by taking the median of this range and multiplying it by the applicants' real income. G_{ij} represents how urban or rural a given census tract is. We discuss the creation of this index later on in the Data section. Additionally, because housing markets are not uniform across different locales, we choose to interact G_{ij} with FMR_{ijt}, the primary form of substitute housing for MHs. We do this because the ratio of MH to low-income apartments for a given area is likely to change based on how urban or rural it is. Especially in expensive areas like the Atlanta metro-area, the availability of low-income apartments is likely to be scarce, and so we isolate the effect of that substitute housing option based on if it is in an urban or rural area. For our regressions, we restrict the data to only include conforming loans for single-family dwellings where the purchased home was intended to be the borrower's new primary residence.[17] We also limit the maximum real income (base year: 1983) of an applicant to \$150,000.

[17] Conforming loans are the most common form of mortgage loans with terms and conditions that meet the funding criteria of Fannie Mae and Freddie Mac. Conforming loans cannot exceed a certain dollar limit, which changes from year to year. They are typically lower interest and applicants usually need a credit score of at least 620 to qualify. Segal, (2021)

4.2 Data

4.2.1 Home Mortgage Disclosure Act (HMDA)

This paper makes use of the new data points from HMDA to offer new insights into the manufactured housing industry using loan data (See Section 5.1 Summary Stats Background). These data points give specific information on MH, detailing dimensions such as the share of borrowers who own their land vs those who don't and must take out a chattel loan. While this dataset allows us to shed light on sectors of the industry that have previously not been examined empirically, it is limited as it only includes individuals who took out loans to finance their home purchases, and thus does not include cash sales. Unlike conventional site-built homes, which are typically too expensive to cover without a loan, manufactured homes are often bought with cash— especially smaller, older homes in less demanded areas or parks. As a result, conclusions drawn from this data cannot be applied to the overall MH market but rather reflect the demand for relatively new and well-maintained MH units.

4.2.2 HUD, LAUS, USA Facts, Zillow, USDA Economic Research Service (ERS)

We use HUD Final Fair Market Rents Documentation System data to get the fair market rents (FMR) for apartments at the 40% rental value for each Metropolitan Statistical Area (MSA). This means focusing on apartments that fall within the bottom 40% of prices for a given MSA. For apartments outside of an MSA, data are generated at the county level. By limiting our lens to apartments at the 40% rental level, we can more accurately assess the true value of substitutable housing for manufactured homes. Data on unemployment are derived from the Local Area Unemployment Statistics program by the US Bureau of Labor Statistics which produces various unemployment statistics at the census tract level. Covid incidence and county population data comes from USA Facts. Merging the two we are able to get daily county-level information on number of reported cases which we can compare with the overall size of the area's population. Following the work of Becker and Yea (2015), we use the Zillow Home Value index to produce data for the typical value of homes that fall between the 5^{th} and 35^{th} percentile for a given MSA. From the ERS, we pull Rural-Area Commuting Area (RUCA) codes at the zip code level which we then map to census tracts using the HUD USPS Zip-Tract Crosswalk Tool. RUCA scores range from 1-10, delineating metropolitan (smallest), micropolitan, small town, and rural (largest) commuting areas based on the size and direction of the largest commuting flows. For our Urbanicity variable, G_{ij}, we designate urban as metropolitan (RUCA 1-3), suburban/peri-urban as micropolitan (RUCA 4-6), and rural as small town and rural (RUCA 7-10).

For the scope of this paper, we will look at a 6-state region in the Southern United States that includes Georgia, North Carolina, South Carolina, Mississippi, Tennessee, and Alabama. These states were chosen due to accessibility of data as well as the fact that the overall popularity of manufactured housing appears to be higher in this region compared to other parts of the country.[18]

5 Summary Statistics

5.1 Summary Stats Background

The two key variables examined for these summary statistics are the aforementioned variables pertaining to manufactured housing listed in the HMDA dataset. The first is the Manufactured Home Secured Property Type which identifies whether a manufactured home loan is a personal property loan, meaning secured by the manufactured home and not land (chattel) or secured by the manufactured home and the land (mortgage) (Table 4). Next,

[18] Schneider et al., (2021) p. 20

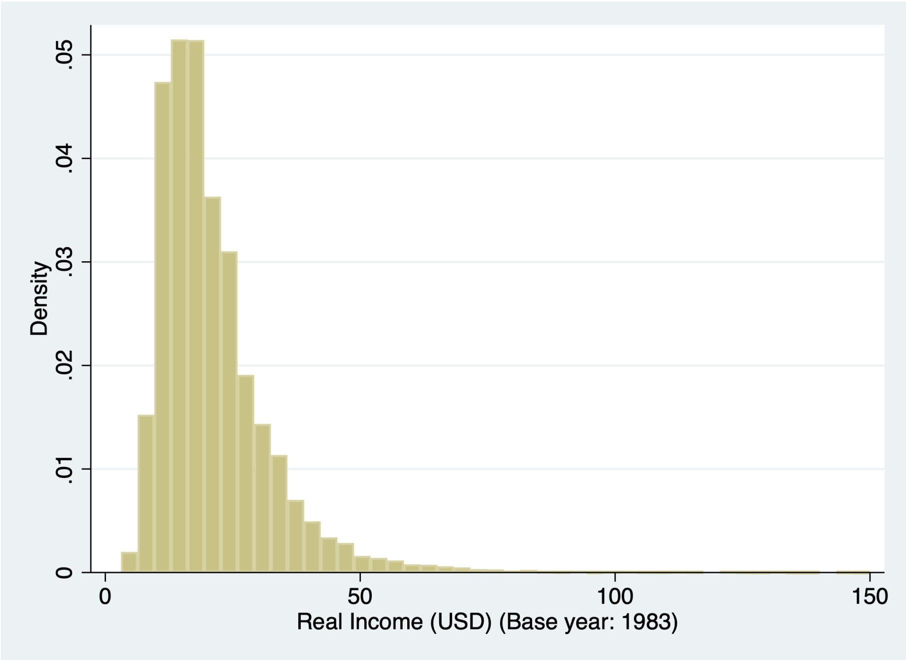
we look at the Manufactured Home Land Property Interest variable which indicates if the land where the manufactured home unit is located is:

a) Directly owned: the borrower owns the land on which the manufactured housing unit is or will be located. b) Indirectly owned: can occur when the borrower is a member of a ROC acting as a housing cooperative where the members of the community collectively own the land where the manufactured housing is located. c) Leased: indicates the borrower is paying rent for the property, which likely means the resident is living in a park where they own or expect to own the structure while paying rent on the lot where the unit is placed. d) Leased without official payments: indicates the borrower is not making rent payments and includes loans where the manufactured home is located on land owned by a family member without a written lease and no agreement to rent payments.

5.2 Summary Stats

Tables 1 and 2 are shown below and showcase statistics from all six of the analyzed states and all forms of housing. As the goal of this paper is to determine the effect on demand of household consumers, for Tables 1 and 2, we again restrict the income of the applicant to be less than $150,000 and only include conforming loans from single-family households who intend to live in the home they are financing. For simplification, Tables 6-13 (See Appendix) show summary stats centered around loan amount. They are generated from the HMDA data, are in nominal terms, look at just manufactured housing, and are given just for the state of Georgia.

Figure 2: Real Income Distribution in 2020 (In thousands)



Based on the income distribution represented in our dataset, we also restrict income to be less than $150,000 annually (Figure 2). For all analyses and regressions in this paper, income is calculated and described in real terms in 1983 dollars.

Table 1: Average Real Income of Borrower by Desired Loan Type

States	Statistic	2018		2019		2020	
	Real Income of Homeowner by Home Type	N	Mean (SD)	N	Mean (SD)	N	Mean (SD)
	(Base year: 1983)		In thousands		In thousands		In thousands
	Site Built	146,944	30.776 (21.389)	164,052	31.815 (22.131)	221,215	34.775 (23.817)
AL	Manufactured House (Mortgage)	6,701	19.109 (11.243)	6,490	19.641 (12.022)	7,335	19.77 (12.064)
	Manufactured House (Chattel)	10,413	17.793 (10.719)	10,998	18.360 (11.383)	13,214	18.306 (10.743)
	Site Built	395,669	34.051 (23.355)	450,974	34.887 (23.756)	602,386	38.540 (26.013)
GA	Manufactured House (Mortgage)	8,685	20.139 (12.414)	9,761	20.395 (12.318)	11,121	20.826 (12.573)
	Manufactured House (Chattel)	6,847	18.795 (11.295)	8,404	19.245 (11.794)	9,653	19.447 (11.301)
	Site Built	70,235	30.561 (21.834)	74,895	31.168 (22.151)	94,377	34.497 (24.407)
MS	Manufactured House (Mortgage)	4,142	20.013 (12.640)	4,557	20.205 (12.362)	5,208	20.528 (13.582)
	Manufactured House (Chattel)	8,448	18.587 (12.203)	10,333	18.664 (11.596)	11,334	18.188 (10.700)
	Site Built	371,083	33.88536 (22.929)	430,441	34.987 (23.803)	609,203	38.56403 (25.834)
NC	Manufactured House (Mortgage)	19,972	18.997 (11.231)	20,935	19.352 (10.916)	23,130	19.893 (11.463)
	Manufactured House (Chattel)	7,052	16.623 (10.516)	8,228	17.131 (10.36)	9,135	17.289 (10.735)
	Site Built	181,369	31.749 (21.792)	209,432	32.545 (22.315)	291,218	35.393 (24.296)
SC	Manufactured House (Mortgage)	11,004	18.77197 (10.987)	11,473	19.244 (11.593)	13,185	19.522 (11.679)
	Manufactured House (Chattel)	8,848	17.735 (11.603)	10,306	18.433 (11.039)	12,198	18.434 (10.569)
	Site Built	247,352	31.804 (22.323)	283,187	32.798 (22.835)	383,411	35.708 (24.764)
TN	Manufactured House (Mortgage)	12,068	18.837 (11.587)	12,105	19.012 (11.579)	12,986	19.890 (12.199)
	Manufactured House (Chattel)	5,386	17.398 (11.418)	5,459	18.153 (11.384)	6,224	18.576 (12.708)

Table 1 illustrates the change in real income over the time span of our analysis for individuals who applied for loans for site-built or manufactured homes. Among those who sought to purchase manufactured homes, we also differentiate between whether they financed the home through a standard mortgage loan or a chattel loan. We see in Table 1 that for site-built homes in all states, real income increases slightly from 2018 to 2019, and more drastically from 2019 to 2020. For manufactured homes, income either does not change significantly over time, or only increases slightly. The average income of individuals who apply for site-built home financing is typically around \$10,000—\$15,000 greater than their manufactured home desiring counterparts. Borrowers who apply for chattel loans also are seen to have slightly lower incomes than those who apply for standard mortgages.

Table 2: Share of Loans as % of Analyzed Loans (All States)

States	Statistic	2018		2019		2020	
	Share of Loans for Home Type	N	Share	N	Share	N	Share
AL	Site Built	147,278	89.58%	164,471	90.39%	222,037	91.53%
	Manufactured House (Mortgage)	6,705	4.08%	6,493	3.57%	7,337	3.02%
	Manufactured House (Chattel)	10,418	6.34%	11,000	6.05%	13,220	5.45%
GA	Site Built	396,784	96.23%	452,390	96.14%	604,974	96.68%
	Manufactured House (Mortgage)	8,692	2.11%	9,765	2.08%	11,130	1.78%
	Manufactured House (Chattel)	6,853	1.66%	8,407	1.79%	9,658	1.54%
MS	Site Built	70,495	84.84%	75,162	83.46%	94,844	85.14%
	Manufactured House (Mortgage)	4,146	4.99%	4,558	5.06%	5,210	4.68%
	Manufactured House (Chattel)	8,454	10.17%	10,336	11.48%	11,338	10.18%
NC	Site Built	372,140	93.23%	431,658	93.67%	611,608	94.99%
	Manufactured House (Mortgage)	19,981	5.01%	20,946	4.55%	23,143	3.59%
	Manufactured House (Chattel)	7,057	1.77%	8,232	1.79%	9,144	1.42%
SC	Site Built	181,836	90.15%	209,975	90.60%	292,274	92.00%
	Manufactured House (Mortgage)	11,014	5.46%	11,484	4.95%	13,196	4.15%
	Manufactured House (Chattel)	8,857	4.39%	10,312	4.45%	12,206	3.84%
TN	Site Built	248,075	93.42%	284,019	94.17%	384,892	95.24%
	Manufactured House (Mortgage)	12,073	4.55%	12,116	4.02%	12,994	3.22%
	Manufactured House (Chattel)	5,389	2.03%	5,460	1.81%	6,229	1.54%

Table 2 shows the share of all analyzed loans towards three different forms of housing. Based on the results of this table, we would expect that our hypothesis that the pandemic increased demand for manufactured housing is likely to be untrue, as the share of loans for site-built homes for all states is the highest in 2020. However, as these are only summary statistics, they are unable to isolate the effects of the variables this paper focuses on and merely provide a broad outlook on the housing market. Through our regressions, we find results that counter some of the outcomes suggested by our initial summary stats.

6 Results

6.1 Aggregated State Regression Results

6.1.1 Pandemic-Related Results

For our first regression, we use data from all six states to estimate the likelihood of purchasing a MH compared to a site-built home. Regressing our independent MH purchasing probability variable against our predictors listed in Equation 5 — to determine the extent to which the Covid-19 Pandemic changed home purchasing outcomes among individuals, we find results that both support and go against our initial hypothesis (Tables 3-5). Concerning the pandemic and recession-related variables, we see that the 2020 year dummy is significant at the .1% level and yields an odds ratio of 1.59. In other words, compared to 2018, the odds of an individual wanting to finance a manufactured home was 1.59 times greater in 2020. Whereas, in 2019, the odds ratio was 1.2 indicating an individual was still more likely to purchase a manufactured home in 2019 compared to 2018 but not to the same magnitude as in 2020. We also see that the odds ratio of our Covid variable is negative, indicating a one unit increase our County Covid Infection Rate variable multiplies the odds of applying for a MH loan by 0.973, signifying a decrease in likelihood of MH purchase. The reason for this counter-intuitive result is likely due to limitations within our data—specifically a lack of time variation— which is further discussed in the Limitation section. The odds ratios for unemployment and income follow the hypothesis, showing that both falling income and increasing unemployment —albeit only very slightly— increased the likelihood of an individual applying for a MH loan. These results would suggest that certain aspects of the pandemic did to some extent spur demand for manufactured housing.

Table 3: Probability of Applying for Manufactured Home Loan Regression Results (Logistic)

Variable: Manufactured Home	Coefficient (log Odds)	Odds Ratio
Real Income	-0.049***	0.952
(In Thousands)	(0.001)	
Year Dummy (base: 2018)		
2019	0.183***	1.200
	(0.010)	
2020	0.464***	1.590
	(0.029)	
County Covid Infection Rate	-0.028***	0.973
	(0.004)	
County Unemployment Rate	0.015 ***	1.02
	(0.004)	
Urbanicity (base: Urban)		
Suburban/Peri-Urban	-1.440***	0.237
	(0.062)	
Rural	0.239***	1.27
	(0.071)	
Fair Market Rent of Two Bedroom Apartment (FMR)	-.003***	0.997
(40% level)	(0.000)	
Urbanicity X FMR (base: Urban)		
Suburban/Peri-Urban X FMR	.003***	1.003
	(0.000)	
Rural X FMR	.000***	1.000
	(0.000)	
Zillow Bottom Tier Site Built Home Value (5-35% level)	-0.006***	0.994
(In Thousands)	(0.000)	

However, in addition to results that seemingly support our initial hypothesis, we also find additional results that counter it. Counter-intuitively, the odds ratios for both substitutable housing options are below one, suggesting an increase in the cost of comparable housing

Table 4: Probability of Applying for Manufactured Home Loan Regression Results Continued (Logistic)

Variable: Manufactured Home	Coefficient (log Odds)	Odds Ratio
Applicant Race (base: White)		
Black or African American	0.165***	1.179
	(0.011)	
American Indian or Alaska Native	0.941***	2.562
	(0.042)	
Asian	-1.794***	0.166
	(0.066)	
Native Hawaiian or Other Pacific Islander	-0.435***	0.647
	(0.127)	
2 or More Minority Races	0.165	1.180
	(0.101)	
Average Real Debt (base: 0$<5,000$)		
5,000$-<10,000$	-0.444***	0.641
	(0.010)	
10,000$-<20,000$	-0.852***	0.426
	(0.015)	
20,000$-<30,000$	-0.873 ***	0.418
	(0.037)	
30,000$-<40,000$	-0.338 ***	0.713
	(0.087)	
40,000$-<50,000$	0.179	1.196
	(0.205)	
>50,000$	1.216***	3.372
	(0.298)	
Applicant Sex (base: Male)		
Female	-0.182***	0.834
	(0.010)	
Joint (two applicants)	0.524***	1.689
	(0.010)	

Table 5: Probability of Applying for Manufactured Home Loan Regression Results Continued (Logistic)

Variable: Manufactured Home	Coefficient (log Odds)	Odds Ratio
Age Group (base: <25)		
25-34	-0.098***	0.906
	(0.014)	
35-44	0.161***	1.174
	(0.015)	
45-54	0.408 ***	1.504
	(0.016)	
55-64	0.306 ***	1.358
	(0.0.0163)	
65-74	0.036	1.036
	(0.019)	
>74	-0.036	0.964
	(0.030)	
Constant	1.360 ***	3.896
	(0.039)	
N	1,493,706	
LR chi-squared(31)	100410.91	
Pseudo R-squared	0.1724	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

lowers the odds of an individual applying for a MH loan.

Looking at our results for Urbanicity we see that the odds ratio for living in a suburban area is 0.237 indicating significantly lower demand for MHs in suburban areas compared to urban locales. However, the odds ratio for rural areas is 1.27, following the conventional understanding that demand for MHs would be greater in rural areas compared to urban ones.

In the average census tract, a 1 dollar increase in the rent of a nearby low-income apartment lowers the odds that you apply for a loan for a MH by 0.3%. However, looking at our interaction term, for a $1 increase in FMR for an apartment in a suburban census tract, the effect of FMR on the probability that you apply for a loan increases by 0.3%. Therefore, these effects cancel out, and so a change in the FMR of a suburban census tract would have no effect on the probability that an individual from that census tract applies for an MH loan. In other words, living in a suburban area upwardly augments the impact of FMR (+.003), but because this augmentation is of the same magnitude as FMR's average downward effect on MH home purchase likelihood (-.003), the effects cancel out.

Holding all else fixed, being in a rural location increased the odds of MH home purchase by 27%. The Rural X FMR interaction term yields an odds ratio of 1 showing us that being in a rural area has no additional effect on the impact of FMR or being in a rural area, so a $1 increase in FMR would still decrease the likelihood of MH purchase by .3% and being in a rural tract would still increase it by 27%.

6.1.2 Demographic Results

We see that, compared to White individuals, Black and American Indian or Alaska Natives are 1.179 times and 2.562 times, respectively, more likely to apply for a MH loan. This follows the patterns detailed in Schneider et al., (2021). Compared to men, women are less likely to seek manufactured housing while couples are more likely to purchase a MH. A couple may be more likely to also have children and therefore be more likely to choose a manufactured home over an apartment as they may desire extra space. Surprisingly, we find that middle-upper aged individuals are more likely to purchase an MH home compared to their oldest and youngest counterparts. Perhaps the reason for this is due to the nature of our data, in that we only look at a population with decent credit who chose to finance their purchase of a manufactured home as opposed to cash purchasing. It could be the case that young individuals may not have access to credit and so may be more likely to purchase MH with cash, while retired individuals may not wish to take on any more debt and just use their savings to buy their MH.

6.1.3 Other Noteworthy Findings

We see that relatively highly indebted individuals, are more likely to apply for a MH loan. Having average real debt holdings of $40,000—$50,000 increases the odds of applying for an MH loan by 1.196 times while holding more than $50,000 in debt increases the odds by 3.372 times.

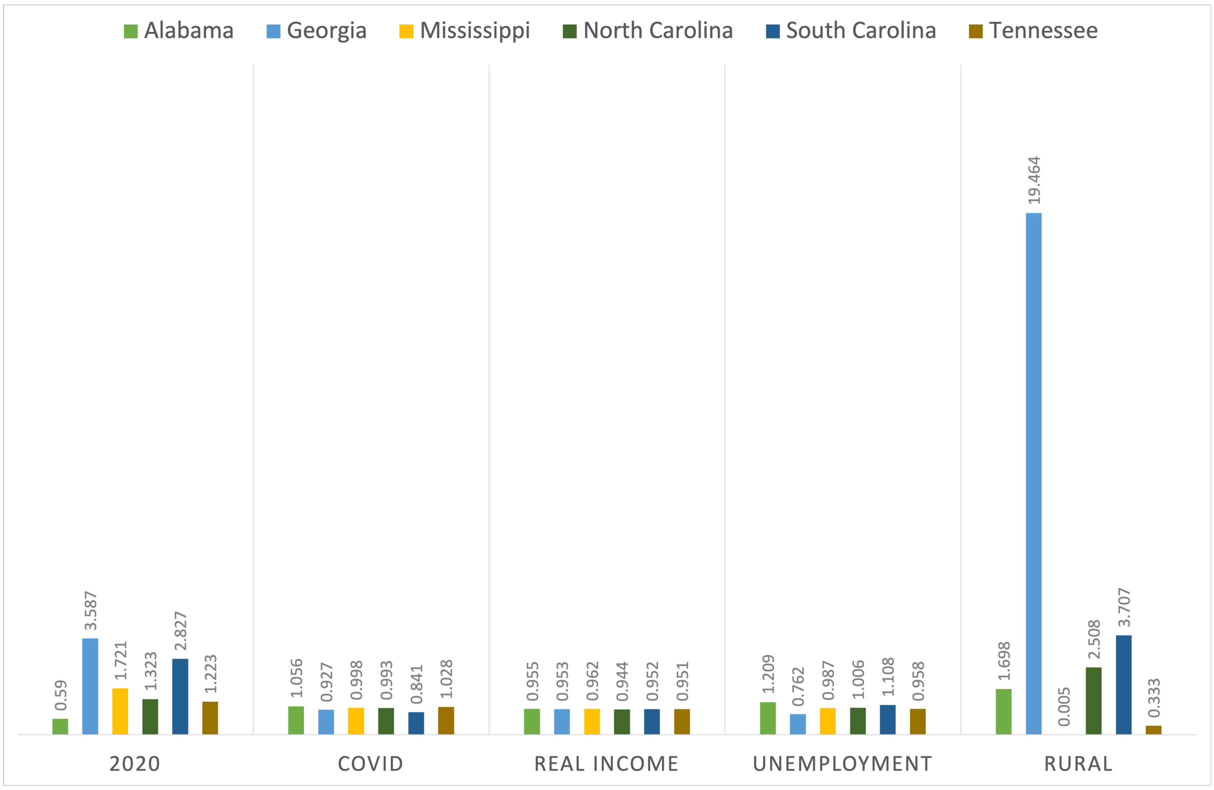
While many of our regression results are highly significant, when extrapolating the results to make predictions on other areas, their explanatory power must be taken with a grain of salt. In the next section we run state-specific regressions where we see a high level of variation in results across different states, suggesting that while a certain pattern may hold for one state, it does not necessarily hold to the same extent for another.

6.2 State-Specific Regression Results

6.2.1 Pandemic-Related Results

For our state-specific analysis, we run the same regression as earlier, with regression only including data from the state being analyzed. Figure 3 shows the odds ratios generated from our regressions predicting the likelihood of applying for a MH loan. It highlights some of the variation across states for some of the variables of focus from this paper. The full regression tables for each state that we generate from this analysis can be found in the Appendix.

Figure 3: Odds Ratios for Selected Key Variables in Each State



First, we see that in every state except for Alabama, the likelihood of applying for an MH loan increased in 2020 compared to 2018. However, the range differs significantly from

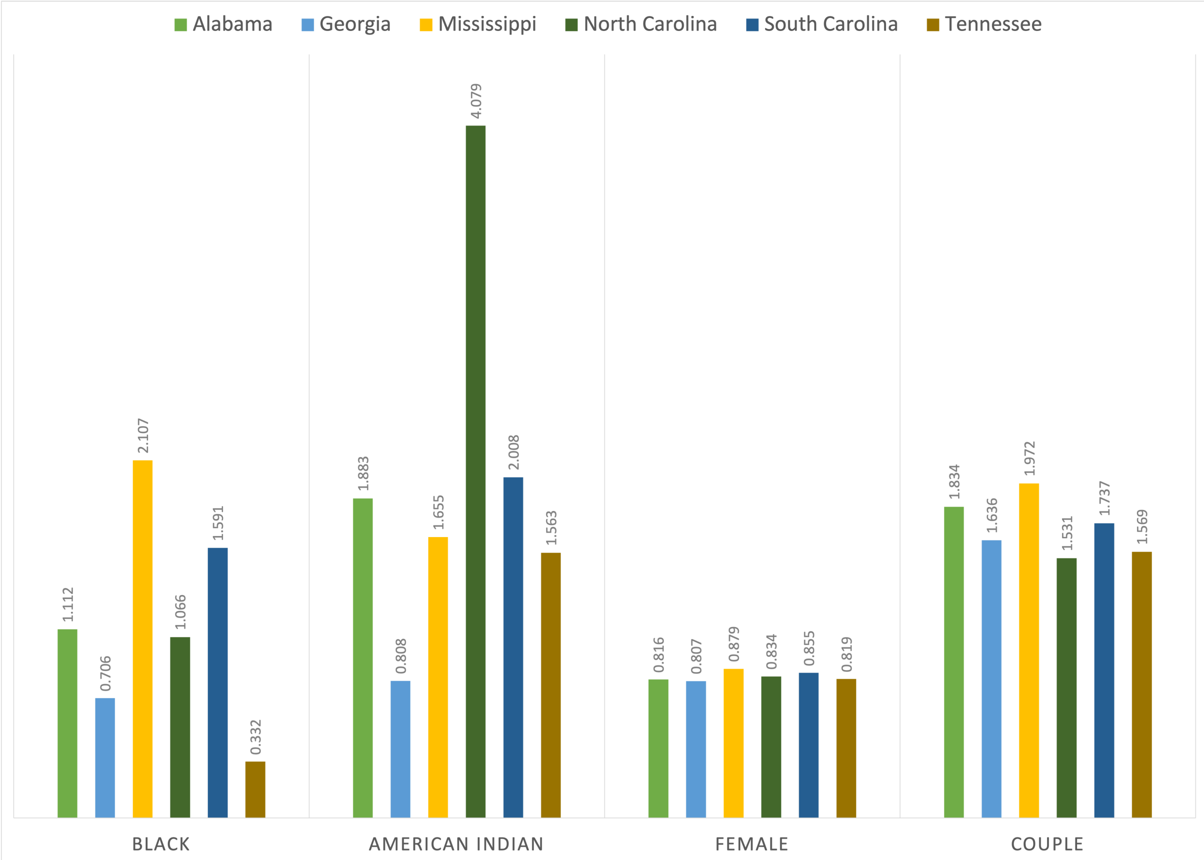
1.223 times more likely in Tennessee to 3.587 times more likely in Georgia. Covid and Unemployment had impacts that were relatively similar across states, sometimes increasing the likelihood of MH purchase while sometimes slightly decreasing it. Surprisingly, the effect of real income is also nearly identical in each state. A $1000 increase in real income lowers the odds of applying for an MH loan by about 5% in each state. For the Rural variable, there is significantly more variation.

In Mississippi and Tennessee, we see that being in a Rural Area relative to an Urban one lowers the likelihood of MH purchase by 99.5% and 67.3%, respectively. Some reasons for these strange results may include omitted variable bias as well as downward bias created from the interaction term with FMR that is included in the regression. When the regression is run without interacting Urbanicity and FMR, the coefficients and odds ratio for Suburban and Rural follow the conventional understanding. Being in a suburban area increases the likelihood of MH purchase slightly and being in a rural area increases it even more. However, the interaction term was left in the regression as it was still highly significant. We see that for Alabama, Georgia, North Carolina, and South Carolina, being in a rural census tract increases the likelihood of applying for a MH loan significantly — especially in Georgia. In the case of Georgia, being in a rural tract compared to an urban one increases the odds of applying for a MH loan by over 1900%. It is likely that because the metro-area of Atlanta is so large and expensive, manufactured housing in that region is probably either scarce or largely non-existent. If you remove Atlanta, the rest of Georgia's city sizes and population distribution essentially become that of Alabama's. Even so, with an odds ratio that high, it is likely that this odds ratio is biased upwards as well.

6.2.2 Demographic Results

Figure 4 shows the odds ratios for predicting MH loan application for some selected demographic variables. We see significant variation across states for Race but results are

Figure 4: Odds Ratios for Selected Demographic Variables in Each State



more stable for Sex. For Black applicants, we see lower odds in Georgia and Tennessee. One reason for this could be due to the large Black populations that live in metropolitan areas of Atlanta, Nashville, and Memphis. For these states, it could be that since an overwhelming majority of the Black population lives in these urban areas, the likelihood of applying for an MH loan is relatively low compared to other states. With regard to Tennessee, another reason may be that during slavery, Tennessee's land was not as popular for plantation agriculture compared to other states like Mississippi. For a future paper it would be interesting to dive deeper into the racial implications of manufactured housing, and even how mapping MH ownership across the country could give information on historical migration and settlement patterns among Black and other minorities in America. Another figure that jumps out is the effect of being American Indian or Alaska Native on the odds of applying for an MH loan in North Carolina. The large odds ratio here is likely due to the large Native American population that exists —like the Lumbee Tribe— in the more rural areas of North Carolina like Robeson, Hoke, Cumberland, and Scotland counties.[19]

7 Additional Analysis: Probability of Living in a MHC

First, we follow the tree shown in Figure 1 and try to find the likelihood that, conditional on wanting a manufactured home, an individual chooses to live in a manufactured housing community or park. An assumption of our paper is that anyone who is paying rent on the land beneath the home they are purchasing is living in a MHC. We regress our independent MHC home purchasing probability variable against the same predictors from Equation 5, limiting the data to only include MH loans (See Tables 32-34 in Appendix). Compared to prior analysis, this regression yields far more statistically insignificant results, suggesting that there are additional factors that would go into deciding to live in a park that we are unable to account for in this paper. However, there are some interesting findings of statistical significance.

We see that the 2020 variable yields an odds ratio of 0.544 meaning the odds of someone applying to purchase a MH in a MHC in 2020 was 56.4% lower when compared to 2018. In 2019, the odds were only 7.6% lower. This could be because homes in developed parks are typically more expensive and so given increased financial pressures, fewer individuals could afford to live in them. This may also support evidence for claims discussed in the introduction that MHCs are being bought by large corporations and are becoming increasingly

[19]See more information about the Lumbee Tribe at https://www.lumbeetribe.com

difficult and expensive to live in.

The higher an individual's income, the less likely they are to live in an MHC — but only slightly. An individual from a county with higher Covid infection rates and higher unemployment is also slightly more likely to have applied for MHC housing. Our results also show that compared to Non-Hispanic Whites, minorities are all more likely to live in MHC. Compared to men, women and couples are also more likely to live in MHC. One reason could be that compared to single men, single women may be more likely to have children and therefore demand a safer and more spacious environment that can be provided by living in MHCs. Older individuals are also more likely to live in MHCs. Compared to individuals below 25, being 74 and over increases the odds of applying for a home in an MHC by 1.863 times. As these results seemingly support the idea that MHs in MHCs are more expensive and of better quality than other MHs, we thought it would be interesting to the regression again including data from site-built housing. These results can be viewed in Tables 35-37 in the Appendix.

8 Discussion: Limitations and Possible Improvements

8.1 Dataset Analysis

The largest limitation of this study is that our main dataset is for only three years and only goes up to 2020. Although the pandemic began in March 2020, most cases occurred in 2021.[20] With respect to changes in housing, one could expect significant time lags from the beginning of the pandemic to when someone decides to move. As a result, with data only spanning the end of 2020, we are only able to study individuals who might have quickly decided to change houses after the onset of Covid. Many people who bought homes in 2020 had likely been planning to do so before the pandemic began. With 2021 loan data

[20] See 'Daily New Cases in the United States' graph at https://www.worldometers.info/coronavirus/country/us/

expected to be published later in 2022, this analysis could be done in the future where more data points are available, perhaps resulting in more robust conclusions about the impact of Covid. Additionally, we do not have monthly data. Theoretically, instead of looking at the total end of year percentage of the population who contracted Covid, it would be more beneficial to look at more granular information such as monthly covid incidence rates or months since the Pandemic started. However, the HMDA loan dataset is aggregated at the yearly level. We do not know the date or month the loan application took place, only the year. As a result, although we had more granular timed information for many of our independent variables such as unemployment and Covid incidence rate, we had to average them at the yearly level, weakening our ability to explain the true impact the pandemic had on the MH housing market. Additionally, as mentioned in the Data section, the dataset does not include cash sales. Research shows that manufactured housing buyers are more than three times as likely to purchase a home with cash than buyers of site-built units (37% vs. 11%, respectively).[21] With such a large proportion of MH homes being bought in cash, the results of this paper cannot be expanded to draw conclusions on the MH market as a whole.

8.2 Regression Analysis

Due to the problems outlined above, we were unable to incorporate the role of the government into our analysis. For example, knowing when government stay-at-home orders occurred would be beneficial in understanding the general level of austerity that a given locale was under. Additionally, being able to incorporate when and how long assistance policies like eviction and rent collection moratoriums were implemented would also be useful in analyzing the impact of the pandemic on the MH housing market.

Furthermore, while we find results showing that odds of applying for an MH loan in-

[21] Riley et al., (2021) p 29

creased in 2020 and that MH demand is higher in rural areas, our dataset does not allow us to track the movement of individuals. One of the goals of this paper was to see if people were actively exiting urban areas to suburban and rural locales to purchase manufactured homes. While our results provide some evidence to answer that question, we still do not know where the applicant lived beforehand relative to where the newly purchased home would be located.

9 Conclusion

From the outset, this paper sought to measure the impact of the Covid-19 Pandemic on the demand for Manufactured Housing. I sought to answer this question by looking at demand at the individual level and proxying demand with the likelihood an individual applies for an MH loan over a site-built one. Largely due to a lack of data, this goal proved to be quite challenging. Despite its limitations, the results of this paper show that on average, the odds of an individual applying for a MH loan in 2020 were greater by about 59% when compared to 2018. As individuals earn less income and unemployment goes up, demand for MH increases. Additionally, we see that the impact of Covid infection rates on MH demand depend on the state. This paper is also valuable in that it provides evidence that factors that influence demand for manufactured housing markets may vary significantly by state, even when controlling for other geographic factors.

References

Becker, C. and Garcia Lemus, B. “Little Trailer Park on the Prairie: Determinants of Site Rents in Parks in the Great Plains and Rocky Mountain States”. Economic Research Initiatives at Duke (ERID) Working Paper No. 292 (Oct. 2019).

Becker, C. and Rickert, T. “Zoned Out? The Determinants of Manufactured Housing Rents: Evidence from North Carolina.”. Journal of Housing Economics (2019).

Becker, C. and Yea, A. “The Value of Manufactured Housing Communities: A Dual-Ownership Model”. Economic Research Initiatives at Duke (ERID) Working Paper 196 (Oct. 2015).

Choi, J. H., Goodman, L. “22 Million Renters and Owners of Manufactured Homes Are Mostly Left Out of Pandemic Assistance”. Urban Institute (Aug. 2020).

Kuk, J., Schacter, A., Faber, J. W., Besbris, M. “The COVID-19 Pandemic and the Rental Market: Evidence From...”. (Mar. 2021).doi: 10.1177/00027642211003149.

Parolin, Z., Curran, M., Matsudaira, J., Waldfogel, J., Wimer, C. “Monthly Poverty Rates in the United States during the COVID-19 Pandemic (Working paper)”. Columbia University (2020).

Riley, S., Freeman, A., Dorrance, J. ”Alternatives to Mortgage Financing for Manufactured Housing”. Center for Community Capital University of North Carolina at Chapel Hill (Aug. 2021)

Schneider, K., Schwartz, N., Russell, J., O’Reilly, E., Melton, N., Leitner, S. “Manufactured Housing Finance: New Insights from the Home Mortgage Disclosure Act Data”. (May 2021).

Scott, G. “How the 2008 Financial Crisis Affected the Banking Sector”. Investopedia (Dec.

2021). Retrieved from: https://www.investopedia.com/ask/answers/033015/how-did-financial-crisis-affect-banking-sector.asp

Segal, T., “Conforming Loan”. Investopedia (Feb. 2022) Retrieved from: https://www.investopedia.com/terms/c/conformingloan.asp.

10 Appendix

Table 6: Loan Amount by Ownership Type 2018 — Georgia

Statistic	N	Mean	Sd.	Median	10%	90%
Loan Amount (Direct) (USD)	12,798	86,367.4	50,846.6	85,000	35,000	135000
Loan Amount (Indirect) (USD)	428	97,219.63	36,880.44	95,000	55,000	145,000
Loan Amount(Paid Leasehold) (USD)	1,825	47,043.84	22,300.24	45,000	25,000	75,000
Loan Amount (Unpaid Leasehold)(USD)	2,112	73,527.46	31,548.69	65,000	35,000	115000

Table 7: Loan Amount by Ownership Type 2019 — Georgia

Statistic	N	Mean	Sd.	Median	10%	90%
Loan Amount (Direct) (USD)	14,839	94,075.41	48,299.37	85,000	45,000	155,000
Loan Amount (Indirect) (USD)	428	92,056.07	40,265.24	85,000	45,000	145,000
Loan Amount(Paid Leasehold) (USD)	2,145	49,256.41	22,065.02	45,000	25,000	75,000
Loan Amount (Unpaid Leasehold)(USD)	2,694	76,510.76	31,435.23	75,000	45,000	115,000

Table 8: Loan Amount by Ownership Type 2020 — Georgia

Statistic	N	Mean	Sd.	Median	10%	90%
Loan Amount (Direct) (USD)	17,328	103,288.9	49,338.19	95,000	45,000	165,000
Loan Amount (Indirect) (USD)	500	110,760	56,167	105,000	45,000	175,000
Loan Amount(Paid Leasehold) (USD)	2,144	53,530.78	26,934.46	45,000	25,000	85,000
Loan Amount (Unpaid Leasehold)(USD)	3,308	82,306.53	32,273.5	75,000	45,000	125,000

Table 9: Loan Amount by Loan Type — Georgia

Statistic	2018 N	Mean(SD)	2019 N	Mean(SD)	2020 N	Mean(SD)
Loan Amount (Home and Land) (USD)	9,892	89834.21(53663.13)	11,099	98682.31(51573.2)	12,799	108599.5(50888.4)
Loan Amount (Home without Land) (USD)	7,282	68691.29(35286.37)	9017	72519.13(34800.11)	10,455	79894.31(38301.74)

Table 10: Loan Amount by Age 2018 — Georgia

	Direct		Indirect		Paid Leasehold		Unpaid Leasehold	
Age	N	Mean(SD)	N	Mean(SD)	N	Mean(SD)	N	Mean(SD)
<25	936	84914.53(35380.18)	46	90217.39(31321.92)	148	42635.14(19807.29)	349	68352.44(26607.93)
25-34	2,954	91679.08 (41834.51)	118	103389.8(38894.34)	553	47712.48 (23348.78)	688	78997.09 (31808.84)
35-44	2,509	90902.75 (43453.77)	90	101111.1 (34663.53)	445	46146.07 (19950.14)	452	76836.28 (32342.95)
45-54	2,471	86363.82 (43556.95)	95	95631.58 (35123.2)	307	51384.36 (24218.95)	275	75654.55 (30726.14)
55-64	1,950	77820.51 (42763.01)	56	92678.57(41076.03)	202	47425.74 (21752.95)	176	67329.55 (33682.97)
65-74	1,101	74745.69 (44005.46)	14	89285.71(36734.87)	105	45095.24 (20023.8)	110	61000 (27434.66)
>74	300	72600 (35549.77)	5	65000 (40620.19)	29	53965.52 (27690.23)	34	59705.88(30174.77)

Table 11: Loan Amount by Age 2019 — Georgia

	Direct		Indirect		Paid Leasehold		Unpaid Leasehold	
Age	N	Mean(SD)	N	Mean(SD)	N	Mean(SD)	N	Mean(SD)
<25	1,199	92931.61 (35576.23)	40	83750(41335.87)	183	46311.48 (20898.14)	424	74127.36(26630.17)
25-34	3,340	99209.58 (41435.8)	128	95078.13(38689.07)	621	49363.93 (21435.34)	851	80769.68 (32036.21)
35-44	2,973	99032.96 (46325.06)	97	91597.94(37524.62)	529	48837.43 (21092.78)	570	79596.49(31504.66)
45-54	2,854	94821.3 (46277.52)	87	93275.86 (41321.4)	415	51867.47 (22281.02)	408	72009.8 (30263.05)
55-64	2,164	86377.08 (43506.16)	40	86000 (40051.25)	235	51595.74 (23559.04)	230	76913.04 (35913.42)
65-74	1,223	82391.66 (49768.53)	21	103095.2(49458.98)	87	51321.84 (26506.47)	138	69057.97 (29189.48)
>74	348	75488.51 (42311.35)	14	89285.71 (47509.4)	36	45277.78 (18591.26)	46	63695.65(28410.38)

Table 12: Loan Amount by Age 2020 — Georgia

	Direct		Indirect		Paid Leasehold		Unpaid Leasehold	
Age	N	Mean(SD)	N	Mean(SD)	N	Mean(SD)	N	Mean(SD)
<25	1,395	100125.4 (41375.67)	48	106875 (45646.95)	165	54090.91(29525.07)	480	76937.5(30647.1)
25-34	4,200	108588.1 (46385.49)	157	118057.3(46652.87)	602	55398.67 (27360.43)	1,090	86577.98 (33082.89)
35-44	3,781	107055 (46483.01)	120	108833.3 (47424.12)	520	54884.62 (26714.54)	731	86217.51 (31967.8)
45-54	3,253	104791 (51205.21)	87	119597.7 (81208.96)	412	53834.95(25346.3)	451	83381.37 (30765)
55-64	2,372	98343.17 (49521.49)	60	95500 (49039.07)	234	53974.36 (24490.85)	259	80366.8(31514.74)
65-74	1,209	92162.94 (48805)	21	99285.71 (72840.33)	114	54210.53(22504.46)	179	70083.8 (28587.9)
>74	361	87714.68 (44457.83)	5	63000 (27748.87)	31	60483.87 (29079.05)	71	62605.63(21677.16)

Table 13: Loan Amount by Race – Georgia

				2018				
Race	Direct		Indirect		Paid Leasehold		Unpaid Leasehold	
29	N 98103.45 (48410.7)	Mean(Sd) 2	N 90000 (35355.34)	Mean(Sd) 5	N 45000 (10000)	Mean(Sd) 5	N 97000 (21679.48)	Mean(Sd) 2 or more
American Indian or Alaska Native	65	83461.54 (33922.28)	3	81666.67 (41633.32)	15	46333.33 (38889.34)	11	67727.27 (26866.67)
Asian	62	87903.23 (43320.65)	5	139000 (35777.09)	17	42647.06 (18884.32)	8	105000 (37416.57)
Black	2214	80031.62 (41590.32)	78	91025.64 (34239.03)	593	47478.92 (20078.22)	516	73585.27 (29804.13)
Joint	154	93051.95 (39689.61)	6	125000 (33466.4)	37	49594.59 (21028.37)	28	66071.43 (24696.57)
Hawaiian or Pacific Islander	12	60000 (36306.77)	0	—	5	43000 (21679.48)	5	83000 (24899.8)
Race N/A	1710	92146.2 (86563.25)	33	102272.7 (41023.83)	336	44315.48 (21156.32)	147	65748.3 (34144.91)
White	8551	86742.49 (42953.04)	301	97225.91 (36661)	817	47876.38 (23987.86)	1392	74224.14 (31871.44)
				2019				
2 or more	28	85000 (42860.67)	2	80000 (21213.2)	9	38333.33 (17320.51)	3	91666.67 (32145.5)
American Indian or Alaska Native	59	89406.78 (44422.39)	4	100000 (23804.76)	13	47307.69 (20878.16)	13	75000 (27988.09)
Asian	61	109098.4 (66991.97)	1	35000 (—)	28	50714.29 (22513.96)	5	117000 (14832.4)
Black	2858	87585.72 (40612.18)	111	83738.74 (35448.22)	684	49429.82 (20336.76)	772	76282.38 (30295.36)
Joint	193	104585.5 (44626.16)	6	91666.67 (43665.39)	38	53157.89 (22523.89)	32	84375 (28048.06)
Hawaiian or Pacific Islander	16	80625 (41467.86)	0	—	2	50000 (35355.34)	7	62142.86 (12535.66)
Race N/A	1911	98856.62 (70045.9)	40	100250 (45459.9)	371	48342.32 (23815.48)	137	66021.9 (29982.46)
White	9712	94818.78 (44786.34)	264	94507.58 (41181.97)	999	49424.42 (22557.96)	1725	77226.09 (31998.87)
				2020				
	N	Mean(Sd)	N	Mean(Sd)	N	Mean(Sd)	N	Mean(Sd)
2 or more	49	103979.6 (55084.97)	1	125000 (—)	17	60294.12 (21539.98)	8	88750 (43073.86)
American Indian or Alaska Native	74	94459.46 (44070.05)	2	30000 (7071.068)	18	58888.89 (33279.37)	5	75000 (14142.14)
Asian	92	110326.1 (54680.91)	3	131666.7 (58594.65)	20	71000 (43817.8)	11	99545.45 (84423.18)
Black	4041	99140.06 (43006.55)	139	95071.94 (44955.64)	712	54087.08 (25571.02)	1027	83208.37 (29158.16)
Joint	264	107234.8 (48277.61)	6	138333.3 (88468.45)	37	53378.38 (17402.67)	37	87162.16 (42238.42)
Hawaiian or Pacific Islander	31	120161.3 (50389.88)	1	165000 (—)	6	55000 (6324.555)	8	71250 (14078.86)
Race N/A	2044	102622.3 (63464.37)	31	99193.55 (46888.11)	463	44589.63 (23466.93)	197	75812.18 (34111.91)
White	10732	104830.4 (48372.54)	317	118343.8 (59124.83)	871	57181.4 (28471.71)	2014	82323.73 (32893.84)

Table 14: Probability of Applying for Manufactured Home Loan — Regression Results (Alabama)

Variable: Manufactured Home	Coefficient (log Odds)	Odds Ratio
Real Income	-0.046***	0.955
(In Thousands)	(0.001)	
Year Dummy (base: 2018)		
2019	0.236***	1.266
	(0.027)	
2020	-0.528***	0.590
	(0.029)	
County Covid Infection Rate	0.055***	1.056
	(0.013)	
County Unemployment Rate	0.190 ***	1.209
	(0.011)	
Urbanicity (base: Urban)		
Suburban/Peri-Urban	-1.722***	0.179
	(0.188)	
Rural	0.529***	1.698
	(0.193)	
Fair Market Rent of Two Bedroom Apartment (FMR)	-0.005***	0.995
(40% level)	(0.000)	
Urbanicity X FMR (base: Urban)		
Suburban/Peri-Urban X FMR	0.003***	1.003
	(0.000)	
Rural X FMR	0.000***	1.000
	(0.000)	
Zillow Bottom Tier Site Built Home Value (5-35% level)	0.002***	1.002
(In Thousands)	(0.000)	

Table 15: Probability of Applying for Manufactured Home Loan — Regression Results Continued (Alabama)

Variable: Manufactured Home	Coefficient (log Odds)	Odds Ratio
Applicant Race (base: White)		
Black or African American	0.107***	1.112
	(0.029)	
American Indian or Alaska Native	0.633***	1.883
	(0.125)	
Asian	-2.271***	0.103
	(0.232)	
Native Hawaiian or Other Pacific Islander	-1.345**	0.261
	(0.510)	
2 or More Minority Races	0.509	1.664
	(0.258)	
Average Real Debt (base: 0$<5,000$)		
5,000$-<10,000$	-0.473***	0.623
	(0.023)	
10,000$-<20,000$	-0.861***	0.423
	(0.036)	
20,000$-<30,000$	-0.979 ***	0.376
	(0.094)	
30,000$-<40,000$	-0.777 ***	0.460
	(0.247)	
40,000$-<50,000$	-0.746	0.474
	(0.719)	
>50,000$	0	(empty)
Applicant Sex (base: Male)		
Female	-0.204***	0.816
	(0.025)	
Joint (two applicants)	0.606***	1.834
	(0.025)	

Table 16: Probability of Applying for Manufactured Home Loan — Regression Results Continued (Alabama)

Variable: Manufactured Home	Coefficient (log Odds)	Odds Ratio
Age Group (base: <25)		
25-34	-0.121***	0.886
	(0.034)	
35-44	0.175***	1.192
	(0.037)	
45-54	0.404 ***	1.498
	(0.039)	
55-64	0.291 ***	1.338
	(0.040)	
65-74	0.085	1.088
	(0.046)	
>74	-0.047	0.954
	(0.074)	
Constant	1.153 ***	3.167
	(0.108)	
N	172,861	
LR chi-squared(30)	11699.88	
Pseudo R-squared	0.1359	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 17: Probability of Applying for Manufactured Home Loan Regression Results (Georgia)

Variable: Manufactured Home	Coefficient (log Odds)	Odds Ratio
Real Income	-0.048***	0.953
(In Thousands)	(0.001)	
Year Dummy (base: 2018)		
2019	0.140***	1.151
	(0.029)	
2020	1.277***	3.587
	(0.078)	
County Covid Infection Rate	-0.076***	0.927
	(0.013)	
County Unemployment Rate	-0.272 ***	0.762
	(0.014)	
Urbanicity (base: Urban)		
Suburban/Peri-Urban	-1.362***	0.256
	(0.165)	
Rural	2.969***	19.464
	(0.360)	
Fair Market Rent of Two Bedroom Apartment (FMR)	-0.003***	0.997
(40% level)	(0.000)	
Urbanicity X FMR (base: Urban)		
Suburban/Peri-Urban X FMR	0.002***	1.002
	(0.000)	
Rural X FMR	-0.003***	0.997
	(0.001)	
Zillow Bottom Tier Site Built Home Value (5-35% level)	-0.013***	0.987
(In Thousands)	(0.000)	

Table 18: Probability of Applying for Manufactured Home Loan — Regression Results Continued (Georgia)

Variable: Manufactured Home	Coefficient (log Odds)	Odds Ratio
Applicant Race (base: White)		
Black or African American	-0.349***	0.706
	(0.033)	
American Indian or Alaska Native	-0.213	0.808
	(0.185)	
Asian	-1.796***	0.166
	(0.159)	
Native Hawaiian or Other Pacific Islander	-0.095	0.910
	(0.296)	
2 or More Minority Races	-0.406	0.666
	(0.330)	
Average Real Debt (base: 0$<5,000$)		
5,000$-<10,000$	-0.360***	0.698
	(0.028)	
10,000$-<20,000$	-0.592***	0.553
	(0.040)	
20,000$-<30,000$	-0.499 ***	0.607
	(0.091)	
30,000$-<40,000$	0.284	1.328
	(0.187)	
40,000$-<50,000$	1.034	2.813
	(0.398)	
>50,000$	2.516***	12.376
	(0.465)	
Applicant Sex (base: Male)		
Female	-0.214***	0.807
	(0.028)	
Joint (two applicants)	0.492***	1.636
	(0.028)	

Table 19: Probability of Applying for Manufactured Home Loan — Regression Results Continued (Georgia)

Variable: Manufactured Home	Coefficient (log Odds)	Odds Ratio
Age Group (base: <25)		
25-34	-0.099**	0.906
	(0.040)	
35-44	0.143***	1.154
	(0.043)	
45-54	0.416 ***	1.515
	(0.044)	
55-64	0.356 ***	1.428
	(0.046)	
65-74	0.053	1.054
	(0.052)	
>74	-0.046	0.955
	(0.085)	
Constant	3.254 ***	25.881
	(0.109)	
N	362,509	
LR chi-squared(31)	21701.26	
Pseudo R-squared	0.2467	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 20: Probability of Applying for Manufactured Home Loan — Regression Results (North Carolina)

Variable: Manufactured Home	Coefficient (log Odds)	Odds Ratio
Real Income	-0.058***	0.944
(In Thousands)	(0.001)	
Year Dummy (base: 2018)		
2019	0.165***	1.179
	(0.020)	
2020	0.280***	1.323
	(0.079)	
County Covid Infection Rate	-0.007***	0.993
	(0.012)	
County Unemployment Rate	0.006 ***	1.006
	(0.010)	
Urbanicity (base: Urban)		
Suburban/Peri-Urban	-0.471***	0.625
	(0.134)	
Rural	0.919***	2.508
	(0.148)	
Fair Market Rent of Two Bedroom Apartment (FMR)	-0.002***	0.998
(40% level)	(0.000)	
Urbanicity X FMR (base: Urban)		
Suburban/Peri-Urban X FMR	0.001***	1.001
	(0.000)	
Rural X FMR	0.000	1.000
	(0.000)	
Zillow Bottom Tier Site Built Home Value (5-35% level)	-0.004***	0.996
(In Thousands)	(0.000)	

Table 21: Probability of Applying for Manufactured Home Loan — Regression Results Continued (North Carolina)

Variable: Manufactured Home	Coefficient (log Odds)	Odds Ratio
Applicant Race (base: White)		
Black or African American	0.064**	1.066
	(0.023)	
American Indian or Alaska Native	1.406***	4.079
	(0.057)	
Asian	-1.863***	0.155
	(0.117)	
Native Hawaiian or Other Pacific Islander	-0.401	0.669
	(0.210)	
2 or More Minority Races	0.165	1.180
	(0.173)	
Average Real Debt (base: 0$<5,000$)		
5,000$-<10,000$	-0.445***	0.641
	(0.019)	
10,000$-<20,000$	-0.960***	0.383
	(0.031)	
20,000$-<30,000$	-0.914 ***	0.401
	(0.081)	
30,000$-<40,000$	-0.243	0.784
	(0.188)	
40,000$-<50,000$	-0.161	0.852
	(0.584)	
>50,000$	0	(empty)
Applicant Sex (base: Male)		
Female	-0.181***	0.834
	(0.020)	
Joint (two applicants)	0.426***	1.531
	(0.021)	

Table 22: Probability of Applying for Manufactured Home Loan — Regression Results Continued (North Carolina)

Variable: Manufactured Home	Coefficient (log Odds)	Odds Ratio
Age Group (base: <25)		
25-34	-0.129**	0.879
	(0.028)	
35-44	0.087***	1.091
	(0.031)	
45-54	0.308 ***	1.361
	(0.031)	
55-64	0.192 ***	1.212
	(0.033)	
65-74	-0.116	0.891
	(0.038)	
>74	-0.128	0.880
	(0.061)	
Constant	0.649 ***	1.914
	(0.087)	
N	400,790	
LR chi-squared(30)	25330.56	
Pseudo R-squared	0.1718	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 23: Probability of Applying for Manufactured Home Loan — Regression Results (South Carolina)

Variable: Manufactured Home	Coefficient (log Odds)	Odds Ratio
Real Income	-0.049***	0.952
(In Thousands)	(0.001)	
Year Dummy (base: 2018)		
2019	0.240***	1.271
	(0.025)	
2020	1.039***	2.827
	(0.124)	
County Covid Infection Rate	-0.173***	0.841
	(0.020)	
County Unemployment Rate	0.103 ***	1.108
	(0.011)	
Urbanicity (base: Urban)		
Suburban/Peri-Urban	-1.578***	0.206
	(0.170)	
Rural	1.310***	3.707
	(0.180)	
Fair Market Rent of Two Bedroom Apartment (FMR)	0.000	1.000
(40% level)	(0.000)	
Urbanicity X FMR (base: Urban)		
Suburban/Peri-Urban X FMR	0.003***	1.003
	(0.000)	
Rural X FMR	-0.001	0.999
	(0.000)	
Zillow Bottom Tier Site Built Home Value (5-35% level)	-0.010***	0.990
(In Thousands)	(0.000)	

Table 24: Probability of Applying for Manufactured Home Loan — Regression Results Continued (South Carolina)

Variable: Manufactured Home	Coefficient (log Odds)	Odds Ratio
Applicant Race (base: White)		
Black or African American	0.464**	1.591
	(0.023)	
American Indian or Alaska Native	0.697***	2.008
	(0.123)	
Asian	-1.620***	0.198
	(0.153)	
Native Hawaiian or Other Pacific Islander	-0.135	0.874
	(0.282)	
2 or More Minority Races	0.402	1.494
	(0.207)	
Average Real Debt (base: 0$<5,000$)		
5,000$-<10,000$	-0.460***	0.631
	(0.023)	
10,000$-<20,000$	-0.896***	0.408
	(0.034)	
20,000$-<30,000$	-1.077 ***	0.341
	(0.089)	
30,000$-<40,000$	-0.775 ***	0.461
	(0.230)	
40,000$-<50,000$	0.101	1.107
	(0.461)	
>50,000$	1.952 ***	7.046
	(0.479)	
Applicant Sex (base: Male)		
Female	-0.157***	0.855
	(0.023)	
Joint (two applicants)	0.552***	1.737
	(0.024)	

Table 25: Probability of Applying for Manufactured Home Loan — Regression Results Continued (South Carolina)

Variable: Manufactured Home	Coefficient (log Odds)	Odds Ratio
Age Group (base: <25)		
25-34	-0.062	0.940
	(0.036)	
35-44	0.248***	1.281
	(0.038)	
45-54	0.518 ***	1.679
	(0.038)	
55-64	0.336 ***	1.399
	(0.039)	
65-74	-0.011	0.989
	(0.044)	
>74	-0.085	0.919
	(0.068)	
Constant	-0.609 ***	0.544
	(0.097)	
N	222,653	
LR chi-squared(31)	15139.95	
Pseudo R-squared	0.1478	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 26: Probability of Applying for Manufactured Home Loan — Regression Results (Mississippi)

Variable: Manufactured Home	Coefficient (log Odds)	Odds Ratio
Real Income	-0.039***	0.962
(In Thousands)	(0.002)	
Year Dummy (base: 2018)		
2019	0.155***	1.168
	(0.034)	
2020	0.543***	1.721
	(0.122)	
County Covid Infection Rate	-0.002***	0.998
	(0.015)	
County Unemployment Rate	-0.013 ***	0.987
	(0.012)	
Urbanicity (base: Urban)		
Suburban/Peri-Urban	-5.210***	0.005
	(0.346)	
Rural	-5.215***	0.005
	(0.306)	
Fair Market Rent of Two Bedroom Apartment (FMR)	-0.011***	0.989
(40% level)	(0.000)	
Urbanicity X FMR (base: Urban)		
Suburban/Peri-Urban X FMR	0.007***	1.007
	(0.000)	
Rural X FMR	0.008***	1.008
	(0.000)	
Zillow Bottom Tier Site Built Home Value (5-35% level)	-0.007***	0.993
(In Thousands)	(0.001)	

Table 27: Probability of Applying for Manufactured Home Loan — Regression Results Continued (Mississippi)

Variable: Manufactured Home	Coefficient (log Odds)	Odds Ratio
Applicant Race (base: White)		
Black or African American	0.745**	2.107
	(0.029)	
American Indian or Alaska Native	0.504*	1.655
	(0.220)	
Asian	-0.954***	0.385
	(0.204)	
Native Hawaiian or Other Pacific Islander	-0.803	0.448
	(0.529)	
2 or More Minority Races	-0.377	0.686
	(0.536)	
Average Real Debt (base: 0$<5,000$)		
5,000$-<10,000$	-0.565***	0.568
	(0.030)	
10,000$-<20,000$	-0.958***	0.384
	(0.045)	
20,000$-<30,000$	-0.920 ***	0.399
	(0.108)	
30,000$-<40,000$	-0.897 **	0.408
	(0.334)	
40,000$-<50,000$	-0.132	0.877
	(0.622)	
>50,000$	0.152	1.164
	1.034	
Applicant Sex (base: Male)		
Female	-0.129***	0.879
	(0.032)	
Joint (two applicants)	0.679***	1.972
	(0.032)	

Table 28: Probability of Applying for Manufactured Home Loan — Regression Results Continued (Mississippi)

Variable: Manufactured Home	Coefficient (log Odds)	Odds Ratio
Age Group (base: <25)		
25-34	-0.225**	0.799
	(0.043)	
35-44	-0.040***	0.961
	(0.046)	
45-54	0.138 ***	1.148
	(0.049)	
55-64	0.120 ***	1.128
	(0.052)	
65-74	-0.187	0.829
	(0.062)	
>74	-0.240	0.787
	(0.108)	
Constant	8.123 ***	3371.331
	(0.227)	
N	76,504	
LR chi-squared(31)	11824.44	
Pseudo R-squared	0.2175	

Standard errors in parentheses

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

Table 29: Probability of Applying for Manufactured Home Loan — Regression Results (Tennessee)

Variable: Manufactured Home	Coefficient (log Odds)	Odds Ratio
Real Income	-0.050***	0.951
(In Thousands)	(0.001)	
Year Dummy (base: 2018)		
2019	0.147***	1.159
	(0.025)	
2020	0.201	1.223
	(0.110)	
County Covid Infection Rate	0.028**	1.028
	(0.011)	
County Unemployment Rate	-0.043 **	0.958
	(0.014)	
Urbanicity (base: Urban)		
Suburban/Peri-Urban	-1.889***	0.151
	(0.139)	
Rural	-1.101***	0.333
	(0.173)	
Fair Market Rent of Two Bedroom Apartment (FMR)	-0.003	0.997
(40% level)	(0.000)	
Urbanicity X FMR (base: Urban)		
Suburban/Peri-Urban X FMR	0.003***	1.003
	(0.000)	
Rural X FMR	0.002	1.002
	(0.000)	
Zillow Bottom Tier Site Built Home Value (5-35% level)	-0.006***	0.994
(In Thousands)	(0.000)	

Table 30: Probability of Applying for Manufactured Home Loan — Regression Results Continued (Tennessee)

Variable: Manufactured Home	Coefficient (log Odds)	Odds Ratio
Applicant Race (base: White)		
Black or African American	-1.102***	0.332
	(0.060)	
American Indian or Alaska Native	0.447**	1.563
	(0.151)	
Asian	-1.564***	0.209
	(0.174)	
Native Hawaiian or Other Pacific Islander	-0.538	0.584
	(0.365)	
2 or More Minority Races	0.209	1.232
	(0.295)	
Average Real Debt (base: 0$<5,000$)		
5,000$-<10,000$	-0.358***	0.699
	(0.024)	
10,000$-<20,000$	-0.722***	0.486
	(0.038)	
20,000$-<30,000$	-0.671 ***	0.511
	(0.095)	
30,000$-<40,000$	0.283	1.327
	(0.191)	
40,000$-<50,000$	0.663	1.941
	(0.462)	
>50,000$	0.000	(empty)
Applicant Sex (base: Male)		
Female	-0.200***	0.819
	(0.026)	
Joint (two applicants)	0.451***	1.569
	(0.025)	

Table 31: Probability of Applying for Manufactured Home Loan — Regression Results Continued (Tennessee)

Variable: Manufactured Home	Coefficient (log Odds)	Odds Ratio
Age Group (base: <25)		
25-34	-0.029	0.971
	(0.037)	
35-44	0.326***	1.386
	(0.039)	
45-54	0.665 ***	1.944
	(0.039)	
55-64	0.566 ***	1.761
	(0.041)	
65-74	0.331 ***	1.393
	(0.046)	
>74	0.232***	1.262
	(0.072)	
Constant	1.486 ***	4.421
	(0.120)	
N	256,977	
LR chi-squared(30)	13937.03	
Pseudo R-squared	0.1518	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 32: Probability of Applying for a MHC Home Loan (Conditional on Wanting a MH) Regression Results (Logistic)

Variable: Manufactured Home Community	Coefficient (log Odds)	Odds Ratio
Real Income	-0.004*	0.996
(In Thousands)	(0.002)	
Year Dummy (base: 2018)		
2019	-0.079*	0.924
	(0.039)	
2020	-0.609***	0.544
	(0.103)	
County Covid Infection Rate	0.061***	1.063
	(0.014)	
County Unemployment Rate	0.040 **	1.041
	(0.013)	
Urbanicity (base: Urban)		
Suburban/Peri-Urban	2.569***	13.051
	(0.230)	
Rural	1.867	6.469
	(0.453)	
Fair Market Rent of Two Bedroom Apartment (FMR)	0.003**	1.003
(40% level)	(0.000)	
Urbanicity X FMR (base: Urban)		
Suburban/Peri-Urban X FMR	-0.003***	0.997
	(0.000)	
Rural X FMR	-0.004***	0.996
	(0.001)	
Zillow Bottom Tier Site Built Home Value (5-35% level)	0.001**	1.001
(In Thousands)	(0.000)	

Table 33: Probability of Applying for a MHC Home Loan (Conditional on Wanting a MH) Regression Results Continued (Logistic)

Variable: Manufactured Home Community	Coefficient (log Odds)	Odds Ratio
Applicant Race (base: White)		
Black or African American	0.639***	1.895
	(0.036)	
American Indian or Alaska Native	1.134***	3.108
	(0.102)	
Asian	0.439*	1.551
	(0.220)	
Native Hawaiian or Other Pacific Islander	1.391***	4.020
	(0.311)	
2 or More Minority Races	1.569***	4.802
	(0.230)	
Average Real Debt (base: 0$<5,000$)		
5,000$-<10,000$	-0.065	0.937
	(0.034)	
10,000$-<20,000$	-0.363***	0.696
	(0.059)	
20,000$-<30,000$	-0.231	0.794
	(0.159)	
30,000$-<40,000$	-0.650	0.522
	(0.472)	
40,000$-<50,000$	-0.388	0.679
	(1.054)	
>50,000$	0.148	1.160
	(1.087)	
Applicant Sex (base: Male)		
Female	0.477***	1.612
	(0.037)	
Joint (two applicants)	0.380***	1.462
	(0.039)	

Table 34: Probability of Applying for a MHC Home Loan (Conditional on Wanting a MH) Regression Results Continued (Logistic)

Variable: Manufactured Home Community	Coefficient (log Odds)	Odds Ratio
Age Group (base: <25)		
25-34	-0.061	0.941
	(0.057)	
35-44	-0.057	0.945
	(0.060)	
45-54	0.132 *	1.141
	(0.060)	
55-64	0.258 ***	1.295
	(0.060)	
65-74	0.329 ***	1.390
	(0.067)	
>74	0.622***	1.863
	(0.093)	
Constant	-5.293 ***	0.005
	(0.136)	
N	70,662	
LR chi-squared(31)	2026.50	
Pseudo R-squared	0.0551	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 35: Probability of Applying for a MHC Home Loan Regression Results (Logistic)

Variable: Manufactured Home Community	Coefficient (log Odds)	Odds Ratio
Real Income	-0.052***	0.949
(In Thousands)	(0.002)	
Year Dummy (base: 2018)		
2019	0.092*	1.097
	(0.037)	
2020	0.026	1.026
	(0.101)	
County Covid Infection Rate	0.024*	1.024
	(0.013)	
County Unemployment Rate	0.019	1.019
	(0.013)	
Urbanicity (base: Urban)		
Suburban/Peri-Urban	1.154***	3.170
	(0.213)	
Rural	0.626	1.870
	(0.437)	
Fair Market Rent of Two Bedroom Apartment (FMR)	-0.000	1.000
(40% level)	(0.000)	
Urbanicity X FMR (base: Urban)		
Suburban/Peri-Urban X FMR	-0.001**	0.999
	(0.000)	
Rural X FMR	-0.001	0.999
	(0.001)	
Zillow Bottom Tier Site Built Home Value (5-35% level)	-0.003***	0.997
(In Thousands)	(0.000)	

Table 36: Probability of Applying for a MHC Home Loan Regression Results Continued (Logistic)

Variable: Manufactured Home Community	Coefficient (log Odds)	Odds Ratio
Applicant Race (base: White)		
Black or African American	0.617***	1.854
	(0.035)	
American Indian or Alaska Native	1.776***	5.906
	(0.094)	
Asian	-1.448***	0.235
	(0.205)	
Native Hawaiian or Other Pacific Islander	0.795**	2.214
	(0.270)	
2 or More Minority Races	1.449	4.260
	(0.197)	
Average Real Debt (base: 0$<5,000$)		
5,000$-<10,000$	-0.495***	0.609
	(0.033)	
10,000$-<20,000$	-1.211***	0.298
	(0.058)	
20,000$-<30,000$	-1.135 ***	0.322
	(0.153)	
30,000$-<40,000$	-1.047 **	0.351
	(0.460)	
40,000$-<50,000$	-0.286	0.752
	(1.009)	
>50,000$	1.552	4.723
	(1.013)	
Applicant Sex (base: Male)		
Female	0.275***	1.316
	(0.038)	
Joint (two applicants)	0.857***	2.356
	(0.010)	

Table 37: Probability of Applying for a MHC Home Loan Regression Results Continued (Logistic)

Variable: Manufactured Home Community	Coefficient (log Odds)	Odds Ratio
Age Group (base: <25)		
25-34	-0.141***	0.868
	(0.055)	
35-44	0.098***	1.103
	(0.058)	
45-54	0.451 ***	1.569
	(0.057)	
55-64	0.496 ***	1.643
	(0.058)	
65-74	0.351	1.421
	(0.063)	
>74	0.568	1.765
	(0.087)	
Constant	-4.099 ***	0.017
	(0.130)	
N	1,444,425	
LR chi-squared(31)	6966.33	
Pseudo R-squared	0.1023	

Standard errors in parentheses

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