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The Foreign-Born and the American Dream: An Analysis of Trends in and Determinants of Immigrant Homeownership

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Abstract

For many Americans, owning a home is an important step in their life journey and constitutes a meaningful component of a person's achievement of the "American Dream." This paper analyzes the extent and possibility of homeownership for foreign-born residents of the United States. This paper utilizes Integrated Public Microdata Series (IPUMS) American Community Survey (ACS) data to analyze trends in immigrant homeownership and evaluate the factors that influence homeownership rates among immigrants. To get a view as to what changes have been occurring over time, this paper looks at data from two separate years: 2006 and 2019. I find a statistically significant homeownership gap between immigrant and native households in both 2006 and 2019. Then, I use a series of regression models to estimate the effects of different determinants of the homeownership rate in an attempt to explain this gap. I find that controlling for socioeconomic characteristics and metropolitan area fixed effects explains most of the gap in both 2006 and 2019, but that there is still a statistically significant adjusted gap of more than five percentage points in both years. My results further suggest that country of origin, year of immigration, citizenship status, linguistic isolation, and the presence of ethnic enclaves all have substantial, statistically significant effects on the probability of immigrant homeownership.

1. Introduction

For many Americans, owning a home is an important step in their life journey. Even if it is true that not everybody aspires to be a homeowner, the vast majority of Americans do—including those who currently rent (by choice or otherwise). A 2019 Freddie Mac survey found that roughly 80% of renters would like to buy a home at some point in the future (Freddie Mac Research, 2019). In the years since the 2008-2009 financial crisis, it seemed to become conventional wisdom that homeownership was becoming less popular among younger Americans (Rexrode, 2019). However, there is some evidence that that trend has been slowly changing since the end of that recession (Myers et al., 2020) and that the Covid-19 pandemic might even be helping to close the homeownership gap between Millennials (those born between 1981 and 1996) and older Americans faster than before (Friedman, 2021). The prevalence of television shows about home purchases and home remodeling should be further evidence of the cultural importance of homeownership in the U.S. As a result, there is no denying the importance of homeownership[1] for Americans of all ages.

There are numerous reasons that homeownership is attractive to people: it provides a sense of security and control over one's life, it confers certain social benefits and serves as a status symbol, it allows the improvement of living conditions, it offers the chance to live in communities that might otherwise be unavailable, and—perhaps most importantly—it confers a number of economic benefits, most notably the opportunity to build wealth over time (McCabe 2018). While renting one's living space does not build any wealth at all, purchasing a home simultaneously provides a place to live *and* serves as a potentially profitable investment. With these benefits in mind, it is not surprising that many people in America seek to become

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[1] Throughout this paper, "homeownership" is to be understood as referring to owner-occupied housing. Thus, the "homeownership rate" is the percentage of occupied housing units owned by their occupants.

homeowners. It likely helps that for many people, the image of having attained the "American Dream" likely entails owning one's own home.

There is also well-documented empirical evidence that children who grow up in homes that are owned by their parents have better outcomes. Beneficial outcomes for children have been demonstrated in terms of health, education, behavior, early pregnancy, future earnings, and cognitive ability (Aaronson, 2000; Boehm & Schlottmann, 1999; Haurin et al., 2002), and it appears that these effects are particularly pronounced for low-income homeowning households (Green & White, 1997; Harkness & Newman, 2003). However, it should be noted that there is some evidence that these benefits are not as large when residential mobility, wealth, dwelling type, and vehicle ownership are controlled for (Barker & Miller, 2009). Still, if there are at least some benefits to children to living in owner-occupied housing, that only serves to further establish the importance of the issue.

In addition to homeownership, immigration is a very large and very important part of the American economy. According to Pew Research, "The United States has more immigrants than any other country in the world. Today, more than 40 million people living in the U.S. were born in another country, accounting for about one-fifth of the world's migrants" (Budiman, 2020). In other words, more than one in ten people in America is an immigrant. This means that studying their choices is likely to yield important implications for the American economy. Given the above established importance of homeownership, studying the homeownership choices of immigrants, the factors that affect those choices, and how immigrant homeownership has changed over time are all important questions. Finding their answers would enable us to draw conclusions regarding what factors explain observed differences (if there are any) between the homeownership of U.S. natives and that of immigrants, while at the same time shedding light on what policies might help to bridge any gap that might exist between the homeownership rates of natives and immigrants (if such an outcome is deemed desirable).

Though achieving homeownership is likely to be important for many immigrants, there are a number of factors that likely put them at a disadvantage compared to natives. For instance, they may not have U.S.-specific skills (such as English proficiency) that are helpful for navigating the mortgage and housing markets. Immigrants also may face legal hurdles that natives do not have to worry about. For example, for immigrants who are undocumented, or who are not citizens, it may be harder—from a legal and paperwork standpoint—to acquire a home. Thus, citizenship status is likely to be an important determinant of the immigrant homeownership rate, too. Given that immigrants from one part of the world are, on average, likely to be different in a whole host of ways (economic, cultural, etc.) than immigrants from another part, it is also reasonable to expect an immigrant’s country of origin to play an important role in determining their homeownership rate. Finally, various demographic factors like age, race, and family size are likely to play a role for the same reason that they affect the homeownership decisions of natives. Because of these unique hurdles, it is not unreasonable to suppose that immigrants are aided by the presence of ethnic enclaves in the area in which they live; the presence of members of their own ethnic group in their community can make it easier for them to get help in navigating the housing market and securing loans.

Much of the literature on this subject (summarized below in Section 2) is dated, focuses on the housing market of a different country, uses a different dataset, or focuses on different determinants of homeownership than I do here. As a result, my research reveals how immigrant homeownership has changed in more recent years (both in isolation and compared to the homeownership rate of natives) and more closely evaluates the impact of factors that have not been as closely discussed in the literature in the past, such as immigrant-specific characteristics like linguistic isolation. Thus, the contribution of this research to the literature on immigrant homeownership should be threefold: it updates the literature by showing what progress has been made (if any) to narrow the native-immigrant homeownership gap in recent years, it focuses on determinants of immigrant homeownership that have not been addressed in detail in the literature, and it evaluates whether the determinants of immigrants homeownership have changed over time.

Put more explicitly, my research questions are:

Firstly, what are the homeownership rates for immigrant and native households in the U.S.? Is there a gap between them? How have their homeownership rates changed in recent years?

Secondly, what are the most important determinants of immigrant homeownership in the U.S.? And how well do those determinants explain any homeownership differential that might exist between natives and immigrants?

Thirdly, have the determinants of immigrant homeownership changed over time, and if so, how?

Section 2 provides a review of the related economics literature, Section 3 provides the theoretical background of the paper, Section 4 presents the empirical research design of the paper, Section 5 displays the results of the research, Section 6 discusses those results, and Section 7 concludes.

2. Literature Review

That there are substantial disparities in homeownership rates between different groups in the U.S. is well established. This is true for some groups even after controlling for various relevant variables such as income, though there are conflicting findings regarding which groups still have lower homeownership rates than whites after controlling for those factors (Coulson, 1999; DeSilva & Elmelech, 2012; Kuebler & Rugh, 2013). There seems to be broad agreement, however, that the black and Puerto Rican populations both have lower homeownership rates than whites even after controlling for the most relevant factors (DeSilva & Elmelech, 2012; Kuebler & Rugh, 2013).

The economic performance of immigrants and their ability to successfully assimilate into the societies of their host countries is a topic that has received considerable attention in the literature. For example, Chiswick (1978) and Borjas (1985, 1994) famously studied the assimilation of immigrants' incomes in the U.S. While Chiswick's research seemed to suggest that immigrants' incomes gradually converged with the incomes of natives over time (Chiswick, 1978), Borjas argued that this effect is much smaller than it appeared in Chiswick's research. Borjas showed this by demonstrating how the effect demonstrated by Chiswick becomes less significant when a cohort study is used instead of a cross-sectional one. The appearance of assimilation in Chiswick's work, he argued, emerged because the relative quality of immigrants' human capital in the cross-section was declining over time, giving the impression that immigrants' incomes increased dramatically over time, when in fact this effect was simply due to differences in the human-capital quality of different waves of immigrants (Borjas, 1985, 1994).

Taking the above research into consideration, we know (1) that there are differences in homeownership between different racial and ethnic groups in the U.S. overall and (2) that immigrants generally have lower incomes than natives and may or may not have trouble assimilating over time. Thus, there is good reason to believe that studying immigrants' homeownership in the U.S. will yield interesting results, particularly since it is likely to be found that their homeownership rate is lower than that of natives and that this homeownership rate likely varies depending on the immigrants' country of origin.

The research that I conduct in this paper is similar to one of Borjas' other articles (2002), this one specifically pertaining to homeownership. His research broadly covered homeownership in the U.S. immigrant population, noting that there existed a homeownership gap between immigrants and natives (with natives having the higher rate) over the period from 1980 to 2000—a gap which widened during that time. In attempting to explain that gap, Borjas found that the national origin mix of the immigrant population and their choice of location in the U.S. were particularly important factors. His attempt to investigate the impact of ethnic enclaves also demonstrated their importance in augmenting immigrant homeownership rates. The finding that the presence of ethnic enclaves increases the immigrant homeownership was replicated and confirmed specifically for Chinese immigrants by Painter et al. (2004). Though Borjas' 2002 research is similar to mine in many ways, his findings are roughly twenty years out of date, he used different data sets than I do (as he did not have access to the American Community Survey, which did not exist at the time), and I focus on a few different variables than he does in order to illuminate different aspects of the issue of immigrant homeownership. Providing an update to the status of immigrant homeownership in the U.S. along the same lines as Borjas should be illuminating, especially in light of the fact that many features of the market have likely changed since the 1980-2000 period. For example, the 2008-2009 financial crisis likely has had a noticeable impact on homeownership and could potentially have impacted immigrants differently than natives. Indeed, there is some empirical evidence that this is, in fact, the case (Painter & Yu, 2014).

Constant et al. (2009) studied immigrant homeownership in Germany and confirmed the finding that immigrants have a lower homeownership rate there, too. Using a two-dimensional composite measure of ethnic identity (which is intended to capture the extent to which immigrants in the sample are attached to the culture of their host country and origin country), the authors find that immigrants who become more ethnically committed to their host countries (i.e., immigrants who "assimilate" or "integrate") are more likely to own homes than those who do not (i.e., immigrants who are either "separated" or "marginalized")—regardless of whether they remain committed to their origin country or not. Thus, this research demonstrates the importance of immigrants' commitment to their host country in determining the likelihood that they will own a home there and shows that factors beyond immigrants' economic characteristics are important for explaining their homeownership decisions (Constant et al., 2009).

A different German study by Sinning (2010) focused on the possibility of immigrant homeownership assimilation over time in that country. Interestingly, what he found is that there is no robust relationship between the amount of time an immigrant has spent in Germany and the probability that they own a home. In other words, Sinning found no evidence of immigrant homeownership assimilation. However, seeing as Germany has different immigration policies and a different housing market than the U.S., this result should not necessarily lead to the expectation that similar findings should obtain in the U.S. But at the very least, Sinning's research demonstrates that there is not necessarily a guaranteed relationship between duration in the host country and an immigrant's probability of owning a home there—at least when using a cohort model like his (Sinning, 2010).

A different study by Myers et al. (1998) gets at the idea of homeownership assimilation in the U.S. They find that a few different temporal factors are all very important for explaining immigrants' homeownership rate: the immigrant cohort of which they are a member, the immigrant's age, and the amount of time they have been a resident of the U.S. The strength of these factors suggests that, as measured by homeownership rates, assimilation does indeed seem to be possible for immigrants to the U.S.—or at least it did at the time the study was published in 1998 (Myers et al., 1998).

Amuedo-Dorantes and Mundra (2013) attempt to gauge the importance of an immigrant's immigration status in determining the homeownership rate in Spain. Perhaps unsurprisingly, they find that a person's immigration status has a profound influence over whether they own a home. Specifically, they find that immigrants who are permanent residents of the EU15 (a group of the first fifteen countries to join the European Union, of which Spain is a member) are the most likely to own a home, while undocumented immigrants are the least likely (with residents of non-EU15 countries and temporary residents being in the middle). Amuedo-Dorantes and Mundra's research therefore establishes yet another non-economic factor that is likely to be important in explaining immigrants' homeownership decisions, demonstrating how legal factors can influence the homeownership rate among immigrants (Amuedo-Dorantes & Mundra, 2013).

Kauppinen and Vilkama (2016) attempted to explain the homeownership gap between immigrants and natives of Finland but focuses only on the Helsinki Metropolitan Area. As the authors note, this geographic restriction provides an advantage in the sense that this study does not have any confounding effects caused by differences in the structures of different housing markets in different regions or different countries, but this limited scope should be kept in mind. What they found is that across all immigrant groups, there was homeownership assimilation over time, but that this process occurred at varying speeds for different groups. In addition, most of the homeownership gap between natives and immigrants could be explained by the economic and demographic characteristics of the different groups (Kauppinen & Vilkama, 2016).

This brief review of the related literature should provide some reasonable expectations about the determinants of homeownership in the American immigrant population. Clearly, characteristics such as legal status, national origin, duration in the U.S., the presence of ethnic enclaves, age, and a number of others should all come together to help explain the extent to which a given household is likely to own their home.

3. Theory

Important for understanding the issue of homeownership is understanding the determinants of households' homeownership decisions. In other words, any analysis of homeownership rates—and why they might differ between different groups—should depend, fundamentally, on housing demand and the factors that influence that demand. One easy way of conceptualizing this comes from the application of neoclassical consumption theory to consumption of housing. This involves several key assumptions. Firstly, the decision-making process of households is supposed to mirror that of individual consumers. In other words, a given household seeks, above all, to maximize its utility—and it does so within the constraints of its income and the prices it faces in the marketplace. Secondly, in this model, the market for housing is conceptualized as a market for homogeneous, unobservable "housing services" rather than a market for heterogeneous individual houses. Thirdly, the market for the homogeneous commodity of housing services is assumed to be perfectly competitive. And lastly, no taxes are levied on house purchases and the asset and capital markets are in equilibrium.

As stated before, following neoclassical consumption theory, each household in the market looks to maximize its utility and faces many choices when they are trying to decide how to spend their income. They can only purchase an amount of goods that fits within the constraints of their income and the prices of the goods they are seeking to purchase, and they must decide which set of goods—including housing—will maximize their utility. As Megbolugbe et al. (1991) put it in their review of the literature on the theory behind housing demand, “The household’s attempt to maximize its utility with respect to housing and nonhousing goods defines its housing demand equation” (p. 382). This equation typically looks something like the following:

$$Q = q(Y, P_h, P_o, T),$$

where Q represents the quantity of housing services that will be demanded and is determined by

- Y, household income
- P_h, the relative price of housing
- P_o, a vector of prices of other goods and services
- T, a vector of taste factors.

As Megbolugbe et al. discuss in their article, the vector of taste factors T has often been deemed dependent on the characteristics of the household. If this is true, and T is a function of a vector of household characteristics, then

$$Q = q(Y, P_h, P_o, H),$$

where H is the vector of those household characteristics like age, race, marital status, and household composition. This provides us with a simplified look at how housing demand looks and provides a framework for thinking about which factors influence housing decisions.

One refinement needs to be made here, however: the above model accounts for the total demand for all housing services—regardless of whether that comes in the form of rented or owned housing—and I am concerned here only with *owner-occupied* housing, and specifically with the percentage of individuals who choose to own their homes rather than rent them. In other words, we need to get from the demand for *all* housing services to the *homeownership* rate (i.e., the percentage of occupied homes that are owned by their occupants). As I established earlier, it seems like owning is the more desirable outcome, but it will be useful to describe exactly what makes the two options different in terms of their delivery of housing services. Firstly, it seems that owning one's home allows for increased flexibility in the sense that owned housing units are easier to modify. One can remodel one's owned house as much as is desired, but this is not the case with (most) rented housing. There may also be some risk associated with the decision to live in rented housing since a landlord can ultimately choose what they want to do with the property and may choose to sell it or evict their tenants. Given that there is a difference in long-term cost between renting and owning, which decision is chosen will depend on various factors facing each household. It is not unreasonable to assume that the same factors that influence the total demand for housing in general are the ones that determine a household's choice between renting and owning; whether a household is willing to undertake the cost of purchasing a home will depend on prices, the household's income, and the preferences of its members. In other words, the same factors from the demand equation above should determine a household's choice between renting and owning, and should therefore explain the homeownership rate.

Since my research concerns the homeownership of immigrants as it relates to natives, a few immigrant-specific features merit particular attention because of their ability to predict differences between those two groups—features that are not explicitly touched upon in the model described above but which deserve attention because of the special role they will be playing in my research. These are duration in the U.S., English language proficiency (proxied by a household's "linguistic isolation"), citizenship status, country of origin, and the presence of ethnic enclaves. All of these seem as if they should influence either the taste factors that affect immigrants' choices or the feasibility of owning a home (which presumably most immigrants would like, but may not be able, to do). These are important because they should help explain any differences in the homeownership rate that might exist between immigrants and natives that are *not* explained by the regular determinants of homeownership in the model discussed above. For instance, we should expect that holding income, housing prices, the prices of other goods, and taste factors (i.e., household characteristics) constant, an immigrant household with poor English language proficiency should be less likely to live in owner-occupied housing than a native household. As a result, these immigrant-specific determinants of homeownership should be added to the model to get a full picture of what factors might explain homeownership differentials between immigrants and natives.

The determinants of homeownership implied by the above model do seem to be supported empirically in the literature; as discussed in the literature review above, many of these factors were found to be significant predictors of immigrant homeownership. In addition, a study by Carliner (1974), though dated, explicitly attempted to empirically uncover the determinants of homeownership and measure the magnitude of their effect. What he found was largely to be expected. For instance, income was significant: for each additional $1,000 that a household earned, their probability of owning a home went up by 1.62 percentage points. The study also evaluated the impact of a number of household characteristics. Household size, for example, was found to be highly significant, with homeownership rates rising with household size. The same goes for marital status: married couples are significantly more likely to own their home than households headed by singles or couples who are not married. Age also makes a substantial difference: the probability that a person owns a home goes up substantially as they age. Carliner also finds a strong relationship between homeownership and race: his regression, which controlled for a host of important predictors of homeownership, estimated a coefficient of -0.17 on a dummy variable indicating whether an individual was black or not. In other words, he found a substantial ownership gap between white and black Americans even after accounting for the other factors deemed important. (Carliner hypothesizes that this is in large part due to discrimination in both the housing and credit markets.) Finally, location of dwelling is found to be significant, with more densely populated areas having lower homeownership rates than less densely populated ones (Carliner, 1974).

For the majority of people, owning a home requires getting a mortgage—in other words, they must be offered a loan in order to be able to reasonably afford a house. (It is unusual for someone to be able to purchase their home outright with no loan.) This is true for both natives and immigrants. As a result, it is expected that, in addition to all the factors considered above, the ability of immigrants to achieve homeownership will depend in part on their ability to receive loans at rates they can afford. This may be more difficult for immigrants a few reasons. Firstly, because immigrants may be relatively new to the U.S. (depending, of course, on how long they have been in the country), holding all else equal, their credit history is likely to be less robust than a native's credit history. In other words, there is less information for a lender to use in order to make an accurate judgment about an immigrant's ability to repay a potential loan. Secondly, there may be some form of discrimination against immigrants in either the housing or credit markets (or both). Thirdly, immigrants (especially those who have not been in the U.S. for a particularly long time) may lack certain U.S.-specific skills that might help them navigate credit markets. And fourth, legal considerations, like citizenship status, might make it harder (all else equal) for immigrants to get mortgage loans than natives.

Ultimately, then, upon reflecting on the literature and certain features of the housing market, we can conclude a few things. Firstly, income should be an important variable in explaining any differences that might exist between the homeownership rates of natives and immigrants. Secondly, certain features of the household—such as marital status, family size, race, and age—should also be important determinants of the probability of homeownership for a given family. Geographic factors, such as the particular area in which a household is looking to purchase a home, should also have a large impact on the homeownership rate, since housing prices and the cost of living vary significantly across metropolitan areas. Those features apply to natives and immigrants alike, and their effects should be similar.

For immigrants specifically, we should expect to see duration in the U.S. to be a particularly important explanatory variable for homeownership. The more years an immigrant has spent in the U.S., the more time they have had to develop a credit history, start a family, and settle down (and perhaps acquire skills, such as English proficiency skills, that might indirectly help in the search for and purchase of a home). Country of origin should also have an effect: given the drastically different conditions in different countries around the world, immigrants from different countries come to the U.S. should come with different skills, preferences, and demographic features, for example. The presence of an ethnic enclave in an area should also serve to boost the immigrant homeownership rate for immigrants of that ethnicity, given that ethnic enclaves are likely to provide helpful resources to aid immigrants in navigating the home-purchasing process. And lastly, immigrants also face legal obstacles relating to their citizenship status that natives do not have to worry about. Many immigrants in the U.S. today are undocumented, and even documented immigrants must go through a process (which sometimes takes years) to become citizens. These legal considerations regarding immigrants' legal status should also play a role, as the literature review suggested.

Taking this all together, the homeownership rate for immigrants should depend on a whole host of factors discussed above. It is expected that any difference between the homeownership rates of immigrants and natives should be due, at least in part, to differences in these factors. Studying the influence of those different factors—and how they might have changed over time—is the subject of this research.

4. Empirical Research Design

The data used for this research comes from the American Community Survey (ACS), accessed via the Integrated Public Use Microdata Series (IPUMS) (Ruggles et al., 2020). This dataset is well-suited to this research because it provides a large amount of detailed information—such as demographic information, educational information, country of origin, citizenship status, homeownership status, English language proficiency, metropolitan area of residence, years spent in the US, income, and more—on a very large sample of individuals. To capture the trends in homeownership over time, I have chosen to look at two specific years: one pre-Great Recession year, 2006, and one post-Great Recession year, 2019, that are at roughly similar stages of the business cycle. This allows for an interesting comparison of the factors that influence homeownership in different periods and allow me to determine whether there have been substantial changes in those factors for either natives or immigrants over the last decade and a half. The selection of these two years in specific also avoids data from the midst of the

Great Recession (which would come in the years after 2006) and the upheaval that resulted from the Covid-19 pandemic (which would begin almost immediately after 2019). Since the period from 1980 to 2000 has been well-covered by Borjas (2002), I did not see the need to cover that same period for this analysis.

The empirical analysis is conducted in multiple stages. First, I conduct a comparison of descriptive statistics, calculating the overall homeownership rates for both years as well as separate homeownership rates for natives and immigrants. This provides two important pieces of information: firstly, how much of a gap exists between the homeownership rates of natives and immigrants, and secondly, whether that gap has changed since 2006. Getting a broad view of the characteristics of the immigrant population compared to the native population should begin to tell the story about which factors drive the homeownership rate for each of them and allows us to relate this research to previous work in the literature.

After analyzing the descriptive statistics, a series of linear probability OLS regression models is run. The series of regression models is based, in part, on the regression models used in Borjas (2002). The first of these models simply gets at the impact of being an immigrant, and looks like the following:

$$H_i = X_i\beta + Y_i\lambda + I_i\delta + M_{ik}\rho + \varepsilon_i \qquad (1)$$

where H_i is a dummy variable indicating whether a given household i owns the housing unit in which they live; X_i is a vector of non-economic background characteristics for each household i (the size of the household, the number of the household head’s children in the household, and the age, squared age, sex, marital status, and race of the household head); Y_i is a vector representing the characteristics more directly related to being able to purchase a home (log inflation-adjusted household income and the educational attainment and employment status of the household head);

I_i is a dummy simply representing whether a household is headed by an immigrant; and M_{ik} is a vector of metropolitan area fixed effects[2] indicating whether a household lives in metropolitan area k. Thus, the coefficient δ represents the impact of being an immigrant on the probability that one owns their home. Following Borjas (2002), I run this regression for each year separately. The change in the coefficient δ over the two regression estimations therefore represents whether the probability of homeownership for immigrants has changed over the period from 2006 to 2019. These regressions are run once without socioeconomic controls or metropolitan area fixed effects to determine the unadjusted difference in homeownership rates, then once with socioeconomic controls but no metropolitan area fixed effects, another time with the metropolitan area fixed effects but no socioeconomic controls, and a final time with everything listed in regression model (1) included. Comparing the estimates of the coefficient δ for each of those regressions should show how much of the difference in homeownership probability between natives and immigrants is accounted for by differences in socioeconomic characteristics, by metropolitan area fixed effects, and by both simultaneously. As discussed in the literature review, location of residence has been found to be an important determinant of homeownership rates, so it is expected that the metropolitan area fixed effects will capture important differences between the housing markets of different regions.

The next few regression models use the same basic structure but replace the I_i variable with variables for various immigrant-specific characteristics. Each of them is listed below.

$$H_i = X_i\beta + Y_i\lambda + n_i\omega + M_{ik}\rho + \varepsilon_i \qquad (2)$$

Regression model (2) substitutes in n_i, which represents a vector of dummy variables for the twenty countries of origin with the largest number of individuals in the pooled sample of

[2] Wherever I say that I include metropolitan area fixed effects, I mean that I inserted dummy variables for each of the largest twenty metropolitan areas for the pooled sample of both immigrants and natives across both 2006 and 2019. The reference group, therefore, is everyone in the sample outside of the largest twenty metropolitan areas.

2006 and 2019 combined (and a twenty-first dummy capturing all immigrants from countries not in the largest twenty). The reference group for these country-of-origin dummies is natives, meaning that each of the coefficient estimates on these dummies represents the adjusted effect of being from a certain country on one's predicted probability of owning a home.

$$H_i = X_i\beta + Y_i\lambda + D_i\pi + M_{ik}\rho + \varepsilon_i \tag{3}$$

Regression model (3) replaces the immigrant categories with D_i, a vector of variables representing immigrants' year of migration to the U.S. (effectively proxying for the duration they have lived in the U.S.). This should get at the influence of the amount of time that an immigrant household has been located in the U.S. on the probability that they own their home.

$$H_{it} = X_i\beta + Y_i\lambda + C_i\tau + M_{ik}\rho + \varepsilon_i \tag{4}$$

Model 4 replaces the immigrant category with C_i, which is a vector of two variables indicating whether a given immigrant household head is a naturalized citizen or not. This should capture the effect of citizenship on the probability that an immigrant household owns their home.

$$H_{it} = X_i\beta + Y_i\lambda + L_i\psi + M_{ik}\rho + \varepsilon_i \tag{5}$$

Model 5 includes a final way of categorizing immigrants based on immigrant-specific characteristics, this time including L_i, a vector of two dummy variables that indicate whether an immigrant household is linguistically isolated or not. For the purposes of this study, a household is considered linguistically isolated if either (1) no one in the household age 14+ speaks only English at home or (2) no one in the household age 14+ who speaks a language *other* than English at home can speak English "very well." This gets at how effectively the household can communicate with others outside their family or national origin group. Thus, the coefficient ψ in the regression measures the effect of an immigrant household's linguistic isolation on the probability that they own their home.

Each one of the above regression models is run with and without the socioeconomic controls and metropolitan area fixed effects to demonstrate the impact that these additional explanatory variables have on homeownership differentials. Additionally, each regression is run separately for the years 2006 and 2019 to demonstrate any changes in the coefficients that might have arisen over time.

Since the literature has shown that ethnic enclaves are likely to be important influences of the immigrant homeownership rate, I also run a separate regression model to test for the impact of ethnic enclaves. To proxy for the presence of ethnic enclaves in metropolitan areas, I use the "exposure index" used in Borjas (2002). The exposure index is calculated in the following way:

$$S_{jk} = N_{jk} / N_k,$$

where S_{jk} is the exposure index for a household located in metropolitan area k whose household head was born in country j, N_{jk} is the number of immigrants from country j in metropolitan area k, and N_k is the total number of individuals (immigrant or otherwise) in metropolitan area k. Thus, there is an exposure index value for every combination of metropolitan area and national origin group, and it is effectively the proportion of all households in a metropolitan area whose heads belong to a particular national origin group. This variable is used in an immigrant-only regression of the following form:

$$H_{ijk} = X_{ijk}\beta + Y_{ijk}\lambda + n_{ij}\omega + S_{jk}\alpha + M_{ik}\rho + \varepsilon_{ijk} \qquad (6)$$

This regression model is run on a sample that includes only immigrants from the twenty largest national origin groups (in the pooled sample) and only those who live in the twenty metropolitan areas with the largest number of individuals (in the pooled sample) in the United States. So, regression model (6) tests for the impact and significance of ethnic enclaves by estimating the coefficient α_t of the exposure index while controlling for the household's socioeconomic characteristics and the household head's country of origin, as well as metropolitan area fixed effects. As with the other regression models, this model is estimated for 2006 and 2019 separately to track changes over time.

Since the dependent variable in question here is dichotomous, I also test how well these regressions fit a logistic regression model. The results of that logit regression are displayed in Appendix Table B. Since the results of the logit regression do not differ substantially from the results of my linear probability models and the coefficients of the linear probability models are easier to interpret, I elect to use linear probability models throughout the rest of the body of this paper.

5. Results

In this section, I will first display descriptive statistics describing the households in my sample. Then, I will demonstrate the rationale for including metropolitan area fixed effects in my model by displaying homeownership rates and demographic characteristics for the metropolitan areas included in this study. Next, I show overall homeownership rates for both 2006 and 2019 as well as homeownership rates for different groupings of immigrant households based on the immigrant-specific characteristics discussed in this paper. After that, I present the results of my regression analysis.

In the regression analysis section, I first show the effect of accounting for socioeconomic characteristics and metropolitan area fixed effects on the observed homeownership gap between immigrant and native households. I then turn to my investigation of immigrant-specific characteristics and display the results for each of those. Finally, I display the results of my regression analysis of ethnic enclaves using the previously discussed exposure index variable.

Table 1 displays descriptive statistics comparing native and immigrant households[3] across a variety of characteristics, all of which should have some noticeable impact on a household's probability of owning a home. There are several important things to notice here. Firstly, the distribution of homeownership/mortgage status among natives and immigrants, shows us that native households are more likely to own their homes free and clear *and* to have an active mortgage (i.e., to own their home, but not free and clear) than immigrants.[4] Meanwhile, immigrant households are more likely to be renters in both years. Thus, we find our first evidence of a homeownership gap between immigrant and native households—and a fairly substantial one, at that.

Next, native household heads skew older than immigrant household heads for both 2006 and 2019; in both years, native householders are much more likely to be 55 or older, while immigrant householders are much more likely to be younger than 55.

Perhaps somewhat surprisingly, the income distributions for native and immigrant households are remarkably similar; the largest difference between them is in 2019, during which immigrant households were 2.83 percentage points more likely than natives to fall into the $200,000+ income category. This income distribution therefore shows that there does not seem to be a hugely substantial systematic difference between the incomes earned by native and immigrant households.

The sex distribution shows that for both native and immigrant households, female heads became substantially more common in the sample over the period from 2006 to 2019. Indeed,

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[3] Throughout, the term "native household" or "immigrant household" denotes only whether the household *head* is an immigrant or U.S. native. It does not indicate anything about whether the householder's spouse or children are immigrants.

[4] Past this point, this research will not distinguish between homeowners who own their homes free and clear and those who have mortgages (since the focus of this paper is purely on homeownership overall rather than mortgage status), but I thought it would be interesting to display the breakdown here.

among native households, female household heads became just as common as male ones in 2019. For both years, native households are more likely to be headed by women than immigrant households are.

These descriptive statistics also display some noteworthy differences in terms of household size. For both years, native households are far more likely than immigrant ones to be composed of only one or two individuals, while immigrant households are much more likely to contain three or more people. Indeed, this differential extends even to very large households: for both 2006 and 2019, immigrant households are more than three times as likely to have seven or more people in their household. The general trend suggests that households got smaller for both natives and immigrants over the period from 2006 to 2019. Similarly interesting findings are unveiled by looking at the number of the household head's children in a household. For both years, native householders are far more likely than immigrant householders to have zero of their children living in the household. Indeed, the *majority* of native household heads have zero children living in their household. On the other hand, most immigrant households contain at least one of the head's children, if not more. This holds true for both 2006 and 2019. However, both native and immigrant households contain fewer of the householder's children in 2019 than they did in 2006. This is likely a result of the well-documented declining birth rate in the U.S. (World Bank, 2019).

We can see that for both years, native household heads were substantially less likely to be married than immigrant householders. This lines up well with the observation that native households are more often comprised of a single person than immigrant ones.

The race section of Table 1 shows that native householders are much more likely to be white than immigrant ones and slightly more likely to be black. Native household heads are

Table 1. Descriptive statistics: comparing immigrant and native households (%)

	2006		2019	
	Natives	Immigrants	Natives	Immigrants
Homeownership status				
Owned, free & clear	26.66	15.86	30.58	23.99
Owned, not free & clear (active mortgage)	48.53	44.59	42.21	36.61
Home not owned (rented)	24.81	39.55	27.21	39.41
Age				
< 25	3.81	3.45	2.97	2.12
25-34	12.80	18.30	12.52	12.32
35-44	18.01	25.45	13.82	20.22
45-54	21.94	21.89	15.83	22.57
55-64	18.60	14.47	21.55	19.44
> 64	24.84	16.44	33.31	23.33
Income (inflation-adjusted 2019 $)				
< 20,000	14.27	14.64	12.86	13.15
20,000-39,999	17.69	19.36	16.22	16.13
40,000-59,999	15.99	16.35	15.32	14.62
60,000-79,999	13.78	12.94	13.08	11.93
80,000-99,999	10.16	9.23	10.22	9.33
100,000-149,999	15.47	14.17	15.97	15.16
150,000-199,999	6.21	6.34	7.29	7.82
≥ 200,000	6.43	6.96	9.02	11.85
Sex				
Male	55.31	61.56	49.98	56.71
Female	44.69	38.44	50.02	43.29
Household size				
1	27.70	18.25	29.01	19.28
2	36.78	24.88	38.56	27.83
3	15.14	18.22	14.20	18.39
4	12.49	18.84	10.76	17.64
5	5.34	11.13	4.72	9.35
6	1.68	4.94	1.70	4.32
≥ 7	0.88	3.73	1.05	3.19
Number of head's own children in household				
0	62.62	44.95	66.84	48.36
1	17.49	20.71	16.48	21.53
2	13.17	20.29	10.90	19.02
3	4.93	9.59	4.04	7.71
≥ 4	1.79	4.46	1.74	3.39
Marital status				
Married	56.68	66.89	53.69	64.46
Not married	43.32	33.11	46.31	35.54
Race				
White	83.76	27.55	82.01	24.70
Black	9.83	7.46	9.35	7.66
American Indian/Alaska Native	0.74	0.08	0.85	0.06
Asian/Pacific Islander	0.90	24.68	2.99	29.95
Hispanic/Latino	4.78	40.23	6.58	37.63
Educational attainment				
Less than high school	11.94	27.62	6.69	21.18
High school	29.05	20.55	24.85	18.30
Some college	29.75	19.58	31.67	20.24
Bachelor's degree	18.16	17.28	22.01	20.52
Advanced degree	11.11	14.97	14.78	19.76
Employment status				
Employed or NA	63.08	70.10	59.81	70.02
Unemployed	2.64	3.02	1.72	1.84
Not in labor force	34.29	26.88	38.47	28.15
Poverty status				
Above the poverty line	89.09	84.71	89.49	86.53
Below the poverty line	10.91	15.29	10.51	13.47

much more likely to be of Native American/Alaska Native origin. On the other hand, immigrant household heads are far more likely to be Asian/Pacific Islander and Hispanic/Latino. These trends clearly hold for both years under consideration.

In terms of educational attainment, immigrant householders are more likely to reside on the tails of the distribution; for both 2006 and 2019, they are far more likely than native householders to have not completed high school—but they are also more likely than native householders to hold advanced degrees. On the other hand, native household heads are concentrated in middle of the distribution; they are more likely to have a high school diploma (or equivalent), some college, or a bachelor's degree as their terminal level of education. It should be noted, however, that the percentage of householders with a bachelor's degree as their terminal degree is quite close for both years. Educational attainment overall, for native and immigrant household heads alike, increased from 2006 to 2019.

Native householders are less likely to be employed than immigrant householders in both 2006 and 2019. This difference is accounted for mainly by the larger labor force participation rate of immigrant household heads: immigrant household heads are substantially more likely to be in the labor force than native ones. Native household heads are only marginally less likely to be unemployed than immigrant ones for both years.

Finally, immigrant households were slightly more likely to fall below the poverty line for both years, though this gap closed somewhat over the period from 2006 to 2019 (seemingly because a smaller proportion of immigrant households fell below the poverty line in 2019 than in 2006 rather than because more native households fell below the poverty line over that period).

Table 2 shows homeownership and population characteristics for the twenty largest metropolitan areas in the sample (defined the metropolitan areas with the largest number of

Table 2. Homeownership and population characteristics of the largest twenty metropolitan areas

	Overall homeownership rate	Native homeownership rate	Immigrant homeownership rate	Percentage immigrant households	Percent of all native households	Percent of all immigrant households
			2006			
New York-Newark-Jersey City, NY-NJ-PA	60.96	65.99	48.27	28.38	4.46	13.99
Los Angeles-Long Beach-Anaheim, CA	57.97	62.87	49.95	37.94	2.51	12.12
Chicago-Naperville-Elgin, IL-IN-WI	74.54	75.01	72.22	16.83	2.41	3.86
Dallas-Fort Worth-Arlington, TX	70.78	72.60	60.58	15.13	1.74	2.45
Miami-Fort Lauderdale-West Palm Beach, FL	73.06	77.05	66.77	38.80	1.23	6.15
Washington-Arlington-Alexandria, DC-VA-MD-WV	72.26	73.34	67.46	18.43	1.54	2.74
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	76.74	77.48	68.51	8.27	1.70	1.22
Atlanta-Sandy Springs-Roswell, GA	74.51	75.96	64.07	12.20	1.51	1.66
Houston-The Woodlands-Sugar Land, TX	70.64	72.50	63.83	21.47	1.31	2.83
Boston-Cambridge-Newton, MA-NH	69.95	72.84	53.89	15.26	1.42	2.02
Phoenix-Mesa-Scottsdale, AZ	74.50	76.34	63.44	14.21	1.28	1.67
San Francisco-Oakland-Hayward, CA	63.37	64.25	61.25	29.47	1.07	3.52
Detroit-Warren-Dearborn, MI	79.66	80.23	73.90	9.08	1.24	0.98
Tampa-St. Petersburg-Clearwater, FL	76.48	77.03	72.57	12.20	1.06	1.16
Seattle-Tacoma-Bellevue, WA	69.65	70.95	61.83	14.23	1.04	1.37
Riverside-San Bernadino-Ontario, CA	73.90	75.04	70.23	23.80	0.92	2.27
San Diego-Carlsbad, CA	63.62	65.91	56.26	23.76	0.80	1.96
Denver-Aurora-Lakewood, CO	75.07	76.30	63.94	9.96	0.83	0.72
St. Louis, MO-IL	77.90	78.15	71.14	3.56	0.92	0.27
Baltimore-Columbia-Towson, MD	74.58	75.52	63.78	7.98	0.89	0.61
			2019			
New York-Newark-Jersey City, NY-NJ-PA	60.60	64.70	51.86	31.94	4.12	13.52
Los Angeles-Long Beach-Anaheim, CA	55.02	57.23	51.61	39.30	2.53	11.48
Chicago-Naperville-Elgin, IL-IN-WI	71.58	71.97	69.83	18.21	2.26	3.53
Dallas-Fort Worth-Arlington, TX	66.91	68.09	61.65	18.38	1.98	3.11
Miami-Fort Lauderdale-West Palm Beach, FL	67.46	71.76	61.77	43.09	1.16	6.12
Washington-Arlington-Alexandria, DC-VA-MD-WV	70.43	71.36	66.92	20.95	1.67	3.10
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	74.40	75.25	67.09	10.40	1.63	1.32
Atlanta-Sandy Springs-Roswell, GA	72.39	73.02	68.41	13.76	1.56	1.74
Houston-The Woodlands-Sugar Land, TX	68.04	69.64	63.17	24.68	1.34	3.08
Boston-Cambridge-Newton, MA-NH	66.36	69.43	53.06	18.75	1.35	2.18
Phoenix-Mesa-Scottsdale, AZ	70.95	71.73	65.76	13.20	1.39	1.48
San Francisco-Oakland-Hayward, CA	60.10	60.55	59.16	32.64	1.06	3.60
Detroit-Warren-Dearborn, MI	75.71	75.97	73.46	10.06	1.13	0.89
Tampa-St. Petersburg-Clearwater, FL	72.74	73.17	69.77	12.73	1.19	1.21
Seattle-Tacoma-Bellevue, WA	68.30	68.94	65.56	18.68	1.05	1.69
Riverside-San Bernadino-Ontario, CA	69.92	70.34	68.65	24.70	0.93	2.14
San Diego-Carlsbad, CA	60.74	62.23	56.25	24.87	0.74	1.70
Denver-Aurora-Lakewood, CO	72.15	72.90	65.12	9.70	0.95	0.71
St. Louis, MO-IL	76.15	76.48	68.87	4.26	0.91	0.28
Baltimore-Columbia-Towson, MD	73.59	74.25	67.38	9.58	0.83	0.62

individuals in the pooled sample of 2006 and 2019 combined) ranked by size. The first column, which displays the overall homeownership rate in each of the metropolitan areas, demonstrates that homeownership seems to, at least in part, depend on the area in which one lives. This is likely because of differences in the availability of housing as well as the cost of housing; certain cities are much more expensive to live in than others. The second and third columns show the differences in homeownership within those cities between native and immigrant households. For some cities (New York, for example), the gap is quite large, while for others (Chicago, for example) the gap is not very big at all. The fourth column shows the percentage of each metropolitan area that is comprised of immigrants, and the fifth and sixth show the percentage of the total native and immigrant households that live in each metropolitan area. It is worth noting that the New York and Los Angeles metropolitan areas contain an enormous proportion of the total number of immigrant households in the country; for both years, they together contain around a quarter of the total number of immigrant households.

Table 2 thus provides evidence for why the metropolitan area fixed effects will matter in the regressions I run: if immigrants seem to systematically choose to live in metropolitan areas at a higher rate than natives—and, in particular, in ones that have generally low homeownership rates—this trend may help to explain at least part of the gap between the homeownership rates of immigrant and native households in the U.S.

For the estimated effects of specific socioeconomic characteristics and metropolitan areas of residence on a household's predicted probability of homeownership in both 2006 and 2019, see Appendix Table A.

Table 3 shows the homeownership rate for different groupings of households in the sample. The overall homeownership rates for immigrant and native households, for 2006 and

2019, are displayed at the top. As was indicated earlier, the homeownership rate for natives is significantly higher than the rate for immigrants, though this gap seems to have narrowed slightly from 2006 to 2019, primarily because the homeownership rate for natives declined over that time rather than because the immigrant homeownership rate increased.

The rest of Table 3 shows homeownership rates for different sub-groupings of the immigrant sample. The “year of immigration” section demonstrates the apparent impact of assimilation (or, perhaps more simply, time spent in the U.S.) on the probability that an immigrant household owns their home. This shows with remarkable clarity that the homeownership rate for immigrants increases substantially as they spend more time in the U.S. At face value, this seems to suggest that assimilation in terms of homeownership is very much real. This trend can be seen both vertically (within a particular year, householders that have been in the U.S. for longer are more likely to be homeowners) and horizontally (each year-of-arrival cohort has a higher homeownership rate in 2019 than they do in 2006). The only exception to this trend is that the homeownership rate dips slightly when a household head has been in the U.S. for an exceptionally long time, perhaps because very old people tend to move out of their (owned) homes and into (rented) assisted living facilities and other similar types of residences that require rent payments and are not owned by their occupants.

Table 3 also shows that non-citizen household heads are substantially less likely to own their homes than immigrant householders who are naturalized citizens; this gap is around 30 percentage points in both 2006 and 2019. This provides strong preliminary support for my expectation that the legal status of an immigrant can influence the probability that they own their home.

Table 3. Homeownership rates for natives, immigrants, and subdivided immigrant groups by year

	Homeownership Rate (%)	
	2006	2019
All households	73.54	71.26
Native households	75.19	72.79
Immigrant households	60.45	60.59
Immigrant households, by year of immigration		
2015-2019	–	21.35
2010-2014	–	38.75
2005-2009	12.73	48.13
2000-2004	27.36	53.63
1995-1999	47.11	61.42
1990-1994	55.51	64.34
1985-1989	62.82	68.09
1980-1984	68.46	72.55
1975-1979	72.70	75.31
1970-1974	75.47	77.82
1965-1969	77.76	80.15
1960-1964	80.38	80.63
1955-1959	82.96	83.67
1950-1954	82.64	80.81
Pre-1950	79.04	80.26
Immigrant households, by citizenship status		
Citizen	73.35	71.54
Not citizen	44.64	40.47
Immigrant households, by linguistic isolation		
Not linguistically isolated	67.60	64.86
Linguistically isolated	43.11	45.33
Immigrant households, by country of origin		
Canada	75.57	77.06
China	61.74	64.20
Colombia	58.60	56.11
Cuba	67.14	59.77
Dominican Republic	30.38	32.20
El Salvador	52.51	50.50
Germany	77.36	77.10
Guatemala	40.02	37.91
Haiti	54.22	53.30
India	61.02	63.99
Iran	68.89	64.48
Italy	83.47	81.19
Jamaica	64.47	61.64
Korea	55.31	56.92
Mexico	52.43	55.16
Philippines	71.65	68.68
Poland	73.03	76.84
Taiwan	74.57	82.35
United Kingdom	77.55	77.37
Vietnam	70.30	75.10
Number of observations		
Native households	1,032,719	1,117,058
Immigrant households	130,624	159,658
Percent of households that are foreign-born	11.23%	12.51%

Whether a household is linguistically isolated[5] or not also seems to have a profound effect on the probability that they own their home; linguistically isolated households are substantially less likely than non-isolated households to own their homes. This gap was somewhat larger in 2006 than in 2019 because the homeownership rate for non-isolated households decreased slightly over that period while the rate for isolated households increased slightly. What could account for this phenomenon is not clear.

Lastly, the bottom of Table 3 shows homeownership rates for the twenty largest national origin groups. Broadly, European immigrant groups have high homeownership rates, while Latin American immigrant groups tend to have lower homeownership rates. The three highest homeownership rates in 2006 belong to immigrants from Italy, Germany, and the UK. For 2019, the three highest are Italy, the UK, and Taiwan. The lowest three from 2006 are the Dominican Republic, Guatemala, and Mexico. For 2019, the three lowest are the Dominican Republic, Guatemala, and El Salvador. There is no immediately clear time trend overall; some groups' homeownership rates increased over the period while others groups' decreased.

This overview of the raw homeownership data provides cursory support for some of my predictions by showing that time spent in the U.S., legal status, language ability, and country of origin all seem to have a demonstrable effect on a household's probability of owning their home. Since some of these effects are likely caused by the same things, however, a more detailed analysis is warranted to disentangle each of the effects from each other. So, we now turn to the regression models discussed in Section 4.

The first set of models simply tests the significance and magnitude of the effect of being an immigrant on the homeownership rate. Table 4 displays the coefficient estimates of the

[5] Recall that throughout this paper, a household is considered "linguistically isolated" if "no person age 14+ speaks only English at home, or no person age 14+ who speaks a language other than English at home speaks English 'Very well'" (Ruggles et al., 2020).

variable I_i from regression model (1), which is the dummy variable indicating simply whether a given household head is an immigrant or not, for a few different regression specifications. The first row of Table 4 simply shows the raw difference between the homeownership rates of immigrant and native households for each year. As we saw in Table 4, that raw difference is substantial for both years: in 2006, the probability of an immigrant household owning their home was 14.7 percentage points lower than for natives, and in 2019, the probability was 12.2 percentage points lower than natives. As we can see now, those raw differences are both statistically significant. Thus, we have some evidence to suggest that the native-immigrant homeownership gap closed slightly from 2006 to 2019, though the evidence from Table 3 would

Table 4. Homeownership gap between immigrants and natives

Homeownership gap	Year	
	2006	2019
Unadjusted difference	−0.147***	−0.122***
	(0.001)	(0.001)
Controls for socioeconomic characteristics	−0.084***	−0.079***
	(0.001)	(0.001)
Controls for metropolitan area fixed effects	−0.118***	−0.089***
	(0.001)	(0.001)
Controls for socioeconomic characteristics and metropolitan area fixed effects	−0.056***	−0.053***
	(0.001)	(0.001)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are reported in parentheses. The 2006 regressions have 1,163,343 observations. The 2019 regressions have 1,276,716 observations. Regressions that included socioeconomic characteristics controlled for household size, the number of the householder's children in the household, the householder's age and squared age, the householder's sex (defined as a dummy variable indicating if they are female), the householder's marital status (defined as a dummy variable indicating if they are married, regardless of whether the spouse is present or absent), the householder's race (defined as a vector of dummy variables indicating whether they are black, American Indian/Alaska Native, Asian/Pacific Islander, or Hispanic/Latino), the log of household income (adjusted for inflation), the householder's educational attainment (defined as a vector of dummy variables indicating whether their terminal level of education is high school, some college, a bachelor's degree, or an advanced degree), and the householder's employment status (defined as a pair of dummy variables indicating whether they are employed/"N/A" or not in the labor force). Regressions that included metropolitan area fixed effects included a dummy variable for each of the twenty metropolitan areas with the largest number of individuals in the pooled sample of 2006 and 2019 combined.

suggest that this is primarily because the native homeownership rate declined rather than because of any substantive change in immigrant homeownership rates.

The last three rows of Table 4 show how much of this raw difference can be explained by the households' socioeconomic characteristics, how much by metropolitan area fixed effects, and how much by both at the same time. (For those interested in the specific numerical impacts of socioeconomic characteristics and metropolitan area fixed effects on predicted homeownership in a full model with no immigrant-specific variables, see Appendix Table A. For clarity and conciseness, coefficient estimates for those variables are left out of the tables throughout the body of this paper.)

As shown in the second row of Table 4, controlling for socioeconomic characteristics explains much of the homeownership gap; for 2006, it adjusts the homeownership gap from 14.7 down to 8.4 percentage points, and for 2019, it adjusts it from 12.2 down to 7.9 percentage points. The impact of metropolitan area fixed effects is shown in the third row, and these, too, seem to have explanatory power, though perhaps not as much as the socioeconomic characteristics: controlling for them reduces the gap from 14.7 to 11.8 and from 12.2 to 8.9 percentage points, respectively, for 2006 and 2019.

The final row of Table 4 uses the complete model by controlling for both socioeconomic characteristics and metropolitan area fixed effects. With both sets of variables included, the coefficient estimates for I_i become even lower, as expected. When both socioeconomic characteristics and metropolitan area fixed effects are accounted for, the homeownership gap is, in both years, substantially reduced compared to the unadjusted gap; in 2006, the gap is reduced by about 9.1 percentage points, and in 2019, the gap is reduced by about 6.9 percentage points. In both cases, the adjusted homeownership gap between immigrant and native households is no more than 6 percentage points. In other words, after adjusting for each household's socioeconomic characteristics and the metropolitan areas in which they live, the difference between the probability that a native household owns their home and the probability that an immigrant household owns their home is not nearly as great as it would appear when looking at the raw gap; much of that difference is explained by differences in household characteristics and features of the local housing markets (proxied using metropolitan areas) in the places where immigrants and natives choose to live. Still, even after controlling for these factors, there is still a statistically significant homeownership gap in both 2006 and 2019 of more than 5 percentage points.

It is expected, based on both theoretical considerations and the empirical evidence in the literature, that immigrant-specific characteristics should help to explain why a gap remains even after accounting for those controls. One such immigrant-specific characteristic is country of origin (the country in which an immigrant household head was born). For the purposes of this study, I looked at the twenty largest national origin groups (measured by the total number of individuals from each country in the pooled sample of 2006 and 2019 together). These twenty countries of origin are listed in Table 5.

Table 5 shows the coefficient estimates for those national origin groups in two different regression specifications. Regression specification 1 (the first column under each year) represents the raw homeownership gap between that group and natives. The second specification (the second column under each year) represents the adjusted homeownership gap after accounting for the same controls from earlier: socioeconomic characteristics and metropolitan area fixed effects. For reference, this table shows the estimates of regression model (2) from Section 4. Immigrant households from national origin groups outside of the twenty largest ones are controlled for using a single “other country” dummy variable (not listed in Table 5) that captures the effect of all of the unlisted origin countries collectively. Since observations from native households are included in this regression, the reference group for each of the country-of-origin coefficient estimates is native households. Thus, the coefficient estimates shown in Table 5 represent the homeownership gap between natives and immigrants from each of the listed countries.

Under both 2006 and 2019, regression specification 1 shows a wide variety of raw homeownership gaps depending on which country an immigrant came from. This is unsurprising; immigrants come to the U.S. with a wide variety of backgrounds, with different socioeconomic situations and different desired locations of residence. Some national origin groups are likely to be older, some to have more children, some to have higher incomes, some to be more likely to settle in one city than another, and so on. Regression specification 2 seeks to remove the influence of these characteristics on the homeownership gap. Thus, for some national origin groups, controlling for socioeconomic characteristics and metropolitan area fixed effects causes an enormous reduction in the gap. For instance, in 2006, the homeownership gap for Mexican immigrants (which is the largest national origin group in the sample) drops from 22.8 percentage points all the way down to 4.6 percentage points when we control for socioeconomic characteristics and metropolitan area fixed effects. For 2019, it drops from a 17.6 percentage-point gap down to only a 2.4-point gap. The controls and fixed effects also seem to be very good at explaining the gaps for Colombia, the Dominican Republic, El Salvador, Guatemala, and Haiti. For other groups, however, the results are somewhat puzzling. For Indian immigrants, adding in the controls does not affect the homeownership gap at all in 2006 and actually makes it worse in 2019. Part of this is likely a result of the fact that an immigrant’s country of origin captures some important determinant(s) of homeownership that socioeconomic characteristics and metropolitan area fixed effects fail to capture, such as cultural preferences, discrimination, or other immigrant-specific characteristics that have not yet been discussed.

An immigrant household head's year of immigration (or, alternatively understood, the amount of time that an immigrant household head has spent in the U.S.) is one such

Table 5. Homeownership gap by immigrant country of origin

	2006		2019	
Regression specification:	(1)	(2)	(1)	(2)
Country of origin				
Canada	0.004	−0.046***	0.043***	−0.022***
China	−0.135***	−0.075***	−0.086***	−0.010**
Colombia	−0.166***	−0.056***	−0.167***	−0.065***
Cuba	−0.081***	−0.037***	−0.130***	−0.051***
Dominican Republic	−0.448***	−0.225***	−0.406***	−0.207***
El Salvador	−0.227***	−0.018**	−0.223***	−0.039***
Germany	0.022***	−0.024***	0.043***	−0.019***
Guatemala	−0.352***	−0.123***	−0.349***	−0.112***
Haiti	−0.210***	−0.034***	−0.195***	−0.013
India	−0.142***	−0.142***	−0.088***	−0.118***
Iran	−0.063***	−0.075***	−0.083***	−0.092***
Italy	0.083***	0.060***	0.084***	0.048***
Jamaica	−0.107***	0.079***	−0.111***	0.057***
Korea	−0.199***	−0.113***	−0.159***	−0.115***
Mexico	−0.228***	−0.046***	−0.176***	−0.024***
Philippines	−0.035***	−0.051***	−0.041***	−0.081***
Poland	−0.022**	−0.014*	0.041***	0.017*
Taiwan	−0.006	0.053***	0.096***	0.074***
UK	0.024***	−0.037***	0.046***	−0.031***
Vietnam	−0.049***	0.001	0.023***	0.029***
R^2	0.016	0.255	0.013	0.259
Includes socioeconomic characteristics	No	Yes	No	Yes
Includes metro area fixed effects	No	Yes	No	Yes

* p < 0.10, ** p < 0.05, *** p < 0.01. The 2006 regressions have 1,163,343 observations. The 2019 regressions have 1,276,716 observations. Regressions that included socioeconomic characteristics controlled for household size, the number of the householder's children in the household, the householder's age and squared age, the householder's sex (defined as a dummy variable indicating if they are female), the householder's marital status (defined as a dummy variable indicating if they are currently married, regardless of whether the spouse is present or absent), the householder's race (defined as a vector of dummy variables indicating whether they are black, American Indian/Alaska Native, Asian/Pacific Islander, or Hispanic/Latino), the log of household income (adjusted for inflation), the householder's educational attainment (defined as a vector of dummy variables indicating whether their terminal level of education is high school, some college, a bachelor's degree, or an advanced degree), and the householder's employment status (defined as a pair of dummy variables indicating whether they are employed/"N/A" or not in the labor force). Regressions that included metropolitan area fixed effects included a dummy variable for each of the twenty metropolitan areas with the largest number of individuals in the pooled sample of 2006 and 2019 combined. The twenty national origin groups included here were determined based on how many individuals were from each country in the pooled sample of 2006 and 2019 combined; the twenty largest were selected.

characteristic. This determinant, since it is separate from a person's age, should get at the U.S.-specific skills and other benefits that a household accrues by spending more time in the country, such as familiarity with the housing market. It might also indicate the degree to which an immigrant household is "settled in" to the U.S. Finally, an immigrant that has been in the U.S. for longer is more likely to have established a credit history and therefore might be more likely to be approved for a mortgage. Thus, all else equal, it should be the case that the longer one spends in the U.S., the more likely one is to own their home, completely independently of the impact of age.

Table 6. Homeownership gap by immigrant year of immigration

	2006		2019	
Regression specification:	(1)	(2)	(1)	(2)
Year of immigration				
2015-2019	−	−	−0.514***	−0.305***
2010-2014	−	−	−0.340***	−0.171***
2005-2009	−0.625***	−0.378***	−0.247***	−0.106***
2000-2004	−0.478***	−0.268***	−0.192***	−0.071***
1995-1999	−0.281***	−0.122***	−0.114***	−0.036***
1990-1994	−0.197***	−0.068***	−0.084***	0.030***
1985-1989	−0.124***	−0.020***	−0.047***	−0.012***
1980-1984	−0.067***	0.004	−0.002	0.005
1975-1979	−0.025***	0.008**	0.025***	0.009**
1970-1974	0.003	0.016***	0.050***	0.034***
1965-1969	0.026***	0.015***	0.074***	0.047***
1960-1964	0.052***	0.018***	0.078***	0.044***
1955-1959	0.078***	0.032***	0.109***	0.054***
1950-1954	0.075***	0.029***	0.080***	0.016*
Pre-1950	0.038***	0.019***	0.075***	0.019*
R^2	0.029	0.260	0.024	0.262
Includes socioeconomic characteristics	No	Yes	No	Yes
Includes metro area fixed effects	No	Yes	No	Yes

* p < 0.10, ** p < 0.05, *** p < 0.01. The 2006 regressions have 1,163,343 observations. The 2019 regressions have 1,276,716 observations. Regressions that included socioeconomic characteristics controlled for household size, the number of the householder's children in the household, the householder's age and squared age, the householder's sex (defined as a dummy variable indicating if they are female), the householder's marital status (defined as a dummy variable indicating if they are currently married, regardless of whether the spouse is present or absent), the householder's race (defined as a vector of dummy variables indicating whether they are black, American Indian/Alaska Native, Asian/Pacific Islander, or Hispanic/Latino), the log of household income (adjusted for inflation), the householder's educational attainment (defined as a vector of dummy variables indicating whether their terminal level of education is high school, some college, a bachelor's degree, or an advanced degree), and the householder's employment status (defined as a pair of dummy variables indicating whether they are employed/"N/A" or not in the labor force). Regressions that included metropolitan area fixed effects included a dummy variable for each of the twenty metropolitan areas with the largest number of individuals in the pooled sample of 2006 and 2019 combined.

This prediction is precisely what we observe in Table 6, which shows the impact of an immigrant householder's year of immigration on the homeownership gap between that immigration-year cohort and native households. (For reference, this table shows the results of regression model (3) from Section 4). The layout of this table is exactly like the layout of Table 5; the first column under each year shows the raw homeownership gap between that immigrant group and natives, while the second column shows the adjusted gap. What we find falls in line with what we observed earlier in Table 3; more time in the U.S. tends to translate into a higher probability of owning a home. An enormous homeownership gap exists between very recent immigrants and natives, but once an immigrant has been here for a very long time, their probability of owning a home comes to match and then even exceed the overall rate for natives.

Across the board, adjusting for socioeconomic characteristics and metropolitan area fixed effects seems to simply narrow the gap, regardless of which direction the gap is in. This is likely because adding in a household's socioeconomic characteristics controls for things like age, income, marital status, number of children, and so on—characteristics that are likely also related to an immigrant householder's year of immigration. Ideally, then, the addition of the controls should reduce omitted variable bias and more accurately measure the impact of the amount of time an immigrant household head has lived in the U.S. And the results seem clear and convincing; every additional five years spent in the U.S. seems to narrow the adjusted gap between natives and immigrants until the gap no longer exists (and then widens in favor of immigrant households that have been in the U.S. for a long time but narrows again once they have been here for a particularly long time).

Table 7 shows the impact of citizenship status on the probability that an immigrant household owns their home. (For reference, this table shows the results of regression model (4) from Section 4.) The impact of being a citizen on homeownership is quite substantial: when adjusted for socioeconomic characteristics and metropolitan area fixed effects, the impact of being a naturalized citizen almost closes the entire immigrant-native homeownership gap in both 2006 and 2019. Indeed, in both years, an immigrant householder who is a naturalized citizen is actually predicted to have a slightly higher probability of homeownership than a native householder, on average and *ceteris paribus*, though this gap is quite small for both years. On the other hand, immigrant households headed by non-citizens are much more likely to be renters than native households are—evidently even more so in 2019 than in 2006. It should be noted, however, that since this regression is run separately from the country of origin, year of immigration, and linguistic isolation regressions (i.e., none of those other immigrant-specific variables are controlled for in this regression), the impact of those other immigrant-specific features is at least partially reflected in an immigrant's citizenship status. Nevertheless, dividing immigrant households based on the citizenship status of the household head seems to be quite

Table 7. Homeownership gap by immigrant citizenship status

	2006		2019	
Regression specification:	(1)	(2)	(1)	(2)
Citizenship status				
Not citizen	−0.305***	−0.148***	−0.323***	−0.167***
Naturalized citizen	−0.018***	0.013***	−0.012***	0.008***
R^2	0.023	0.257	0.021	0.261
Includes socioeconomic characteristics	No	Yes	No	Yes
Includes metro area fixed effects	No	Yes	No	Yes

* p < 0.10, ** p < 0.05, *** p < 0.01. The 2006 regressions have 1,163,343 observations. The 2019 regressions have 1,276,716 observations. Regressions that included socioeconomic characteristics controlled for household size, the number of the householder's children in the household, the householder's age and squared age, the householder's sex (defined as a dummy variable indicating if they are female), the householder's marital status (defined as a dummy variable indicating if they are currently married, regardless of whether the spouse is present or absent), the householder's race (defined as a vector of dummy variables indicating whether they are black, American Indian/Alaska Native, Asian/Pacific Islander, or Hispanic/Latino), the log of household income (adjusted for inflation), the householder's educational attainment (defined as a vector of dummy variables indicating whether their terminal level of education is high school, some college, a bachelor's degree, or an advanced degree), and the householder's employment status (defined as a pair of dummy variables indicating whether they are employed/"N/A" or not in the labor force). Regressions that included metropolitan area fixed effects included a dummy variable for each of the twenty metropolitan areas with the largest number of individuals in the pooled sample of 2006 and 2019 combined.

explanatorily powerful, thereby lending support to the hypothesis that an immigrant's legal status helps to explain their probability of owning their home.

Table 8 shows the impact of an immigrant household's linguistic isolation on the probability that they own their home. (For reference, this table shows the results of regression model (5) from Section 4.) The results show that for both years, there is a small but statistically significant gap in the probability of homeownership between households that are not linguistically isolated and native households, especially after controlling for socioeconomic characteristics and metropolitan area fixed effects. On the other hand, linguistically isolated households are substantially less likely than native households to be homeowners, though this effect may have dampened slightly in 2019. Again, as above, since immigrant-specific characteristics other than linguistic isolation are not included in this regression model, it may be that linguistic isolation is picking up at least some of the effects of those other variables and therefore that these other effects are being partially reflected in the coefficients of the linguistic

Table 8. Homeownership gap by immigrant linguistic isolation

	2006		2019	
Regression specification:	(1)	(2)	(1)	(2)
Linguistic isolation				
Isolated	−0.321***	−0.148***	−0.275***	−0.121***
Not isolated	−0.076***	−0.026***	−0.079***	−0.036***
R^2	0.018	0.256	0.012	0.258
Includes socioeconomic characteristics	No	Yes	No	Yes
Includes metro area fixed effects	No	Yes	No	Yes

* p < 0.10, ** p < 0.05, *** p < 0.01. The 2006 regressions have 1,163,343 observations. The 2019 regressions have 1,276,716 observations. Regressions that included socioeconomic characteristics controlled for household size, the number of the householder's children in the household, the householder's age and squared age, the householder's sex (defined as a dummy variable indicating if they are female), the householder's marital status (defined as a dummy variable indicating if they are currently married, regardless of whether the spouse is present or absent), the householder's race (defined as a vector of dummy variables indicating whether they are black, American Indian/Alaska Native, Asian/Pacific Islander, or Hispanic/Latino), the log of household income (adjusted for inflation), the householder's educational attainment (defined as a vector of dummy variables indicating whether their terminal level of education is high school, some college, a bachelor's degree, or an advanced degree), and the householder's employment status (defined as a pair of dummy variables indicating whether they are employed/"N/A" or not in the labor force). Regressions that included metropolitan area fixed effects included a dummy variable for each of the twenty metropolitan areas with the largest number of individuals in the pooled sample of 2006 and 2019 combined. A household is categorized as "linguistically isolated" if "no person age 14+ speaks only English at home, or no person age 14+ who speaks a language other than English at home speaks English 'Very well'" (Ruggles et al., 2020).

isolation variables. Still, these results provide support for the idea that the English proficiency of an immigrant household has a demonstrable impact on the probability that they own their home.

As noted, there may be concerns that the coefficient estimates presented in Tables 5 through 8 suffer from omitted variable bias due to the fact that the immigrant-specific characteristics investigated in those regressions might be related to each other. To demonstrate that the immigrant-specific variables investigated in Tables 5 through 8 have a statistically significant impact independently of each other (i.e., to show that they aren't each picking up the effects of the others), I ran homeownership regressions using only observations from immigrant households (i.e., excluding all native households) and including all of the immigrant-specific variables discussed in Tables 5 through 8 while controlling for socioeconomic characteristics and metropolitan area fixed effects. The coefficient estimates for the immigrant-specific variables in this regression are displayed below in Table 9 for both 2006 and 2019. Bear in mind that since this is an immigrant-only regression, the coefficient estimates presented in Table 9 are made relative to immigrant reference groups and hence are not directly comparable to the estimates presented in Tables 5 through 8 (which were made relative to all native households). Specifically, the country-of-origin coefficient estimates are made relative to the Canadian national origin group, the year of immigration estimates are made relative to pre-1950 arrivals, the citizenship estimates are made relative to non-citizen household heads, and the linguistic isolation estimates are made relative to linguistically isolated households.

As we can see, though the coefficient estimates for some national origin groups in both years are not statistically significant in this model (indicating that their adjusted homeownership rates may be similar to those of Canadian immigrants'), many of them retain their statistical significance. In addition, the year-of-immigration estimates remain explanatorily powerful. (The

Table 9. The independent effects of immigrant-specific determinants of homeownership

	2006	2019
Country of origin		
China	0.011	0.042***
Colombia	−0.002	−0.087***
Cuba	−0.022**	−0.074***
Dominican Republic	−0.183***	−0.210***
El Salvador	0.014	−0.041***
Germany	−0.017*	−0.039***
Guatemala	−0.063***	−0.090***
Haiti	−0.021	−0.045***
India	−0.071***	−0.090***
Iran	−0.028**	−0.082***
Italy	0.080***	0.035***
Jamaica	0.075***	0.009
Korea	−0.054***	−0.127***
Mexico	−0.005	−0.028***
Philippines	−0.030***	−0.114***
Poland	0.036***	0.009
Taiwan	0.075***	0.042***
UK	0.01	−0.017*
Vietnam	0.005	−0.012
All other countries (except Canada)	−0.030***	−0.077***
Year of immigration		
1950-1954	−0.007	−0.009
1955-1959	−0.020**	0.025*
1960-1964	−0.048***	0.01
1965-1969	−0.065***	0.011
1970-1974	−0.083***	−0.006
1975-1979	−0.111***	−0.044***
1980-1984	−0.123***	−0.054***
1985-1989	−0.144***	−0.072***
1990-1994	−0.185***	−0.094***
1995-1999	−0.235***	−0.102***
2000-2004	−0.370***	−0.131***
2005-2009	−0.474***	−0.160***
2010-2014	−	−0.204***
2015-2019	−	−0.315***
Citizen	0.091***	0.128***
Not linguistically isolated	0.059***	0.050***
R^2	0.313	0.291
Number of observations	130,624	159,658

* p < 0.10, ** p < 0.05, *** p < 0.01. These regressions were run on a sample of only immigrant households. They included controls for socioeconomic characteristics: household size, the number of the householder’s children in the household, the householder’s age and squared age, the householder’s sex, the householder’s marital status, the householder’s race, the log of household income (adjusted for inflation), the householder’s educational attainment, and the householder’s employment status. They also included metropolitan area fixed effects (i.e., a dummy variable for each of the twenty metropolitan areas with the largest number of individuals in the pooled sample of 2006 and 2019 combined). The reference group for the country-of-origin variables is Canadian immigrants. The reference group for the year-of-immigration variables is pre-1950 arrivals. The reference group for the “Citizen” variable is non-citizen household heads. The reference group for the “Not linguistically isolated” variable is linguistically isolated households.

ones that are not statistically significant are likely so because those cohorts have similar adjusted homeownership rates to pre-1950 arrivals.) Finally, citizenship and linguistic isolation remain statistically significant and appear to have meaningfully large coefficient estimates. Thus, I hope to have demonstrated that even when controlling for all of the immigrant-specific determinants of homeownership at once, they each remain an important aspect of explaining immigrant homeownership in the U.S.

I now turn to the question of the impact of ethnic enclaves on immigrant homeownership. My findings regarding ethnic enclaves are reported in Table 10. To investigate this particular question, I created a sub-sample of my data that contained only immigrant households whose householders were from the largest twenty national origin groups and who lived in the largest twenty metropolitan areas in the sample. Native households were excluded from the sample; instead of focusing on explaining the native-immigrant homeownership gap, this regression specification is intended to get at what impact the presence of other members of an immigrant household head's national origin group has on their probability of homeownership.

Table 10. Effect of ethnic enclaves on immigrant homeownership

	2006	2019
Exposure index coefficient estimate	0.443***	0.268***
Standard error	0.080	0.079
R^2	0.277	0.273
Number of observations	57,364	69,091

* p < 0.10, ** p < 0.05, *** p < 0.01. The sample used for these regressions included only immigrant households that (1) came from the largest twenty national origin groups and (2) lived in the largest twenty metropolitan areas in the sample. Both regressions were run with controls for country of origin, controls for socioeconomic characteristics (household size, the number of the householder's children in the household, the householder's age and squared age, the householder's sex, the householder's marital status, the householder's race, the log of household income, the householder's educational attainment, and the householder's employment status, all defined in the same way as the previous regressions) and metropolitan area fixed effects. Observations of native households were excluded from this regression because the concept of ethnic enclaves does not apply to them in the same way that it does for immigrant households.

As described in Section 4, the "exposure index" value that was assigned to each household was equal to the proportion of their metropolitan area that was comprised of immigrants from their country of origin. This variable was regressed against homeownership with a slew of other controls, as laid out explicitly in regression model (6) in Section 4.

The findings reported in Table 10 fall largely in line with expectations: as the exposure index associated with an immigrant householder's national origin group and metropolitan area of residence increases, so does the probability that they own their home. In other words, the greater the presence of ethnic enclaves in the area of one's residence (as proxied by the exposure index), the greater the likelihood that one owns one's home. This finding holds for both 2006 and 2019, though there is an interesting differential in the magnitude between the two years. At face value, the larger coefficient estimate for the exposure index variable in 2006 might suggest that ethnic enclaves had a greater impact on an immigrant household's probability of homeownership then that it has in recent years, though this research is in no position to make such a claim conclusively. Nevertheless, the magnitudes of the coefficients, while not enormous, are large enough to warrant attention. The 2006 estimate suggests that on average and *ceteris paribus*, a 1 percentage-point increase in the exposure index is associated with a 0.443 percentage point increase in one's probability of owning a home. For 2019, that figure is 0.268 percentage points. Though this effect might seem small, it provides relatively strong support for the idea that the presence of ethnic enclaves—to the extent that it can be proxied by this exposure index measure—does indeed increase the probability of immigrant homeownership.

6. Discussion

The raw homeownership rates for both 2006 and 2019 showed that there is indeed a gap in homeownership between natives and immigrants, with natives having a substantially higher raw homeownership rate than natives. The preliminary evidence suggested that this gap may have shrunk over the period from 2006 to 2019, though if this is the case, it seems to have been a result of declining homeownership among native households rather than because of increasing immigrant homeownership.

Broadly, the results presented above fell in line with my expectations. My overview of descriptive statistics showed differences between immigrant and native households in terms of a slew of socioeconomic characteristics that I expected to be relevant for helping to explain differences in homeownership between the groups. I found systematic differences within the sample between immigrant and native educational attainment, household size, number of children, race, and marital status, all of which were expected to help explain differences in homeownership. In addition, Table 2 displayed differences in terms of where immigrant and native households are located; immigrant households were shown to be more likely to live in the largest cities in the sample while natives were found to be much more spread out. This, in combination with apparent differences in homeownership depending on what metropolitan area a household is in, lent support for the expectation that controlling for metropolitan area of residence would aid in explaining homeownership differences.

Using regression analysis, I found that this homeownership gap between natives and immigrants was statistically significant in both 2006 and 2019. However, it was speculated that this gap might be at least partly explainable by differences in socioeconomic features between native and immigrant households, as well as differences in what metropolitan areas they tend to live in. So, before considering the influence of immigrant-specific factors, I demonstrated that controlling for household socioeconomic characteristics and including metropolitan area fixed effects both independently and together helped to explain a substantial portion of this homeownership gap in both years. However, in both years, a small gap did remain even after controlling for socioeconomic characteristics and metropolitan area fixed effects. To help explain this remaining gap, I conducted additional regression analyses to investigate the influence of immigrant-specific characteristics.

My analysis of the impact of immigrant-specific characteristics was illuminating. I demonstrated that an immigrant household's country of origin, year of immigration, citizenship status, and linguistic isolation were all statistically significant predictors of homeownership. The findings regarding country of origin suggest that there is enormous variation in the homeownership rates of immigrant households depending on the national origin of the household head, even after controlling for metropolitan area of residence and socioeconomic characteristics. These national origin effects are somewhat more ambiguous than many of the other variables analyzed in this paper given that there is a less direct theoretical link between what country one comes from and homeownership than, say, income or amount of time spent living in the U.S. Nonetheless, it is reasonable to suppose that one's national origin may be related to discrimination faced in the U.S. housing/mortgage markets, cultural preferences, or the amount of wealth that one has access to upon arriving in the U.S. The national origin effects I discovered here were statistically significant even after controlling for socioeconomic characteristics and metropolitan area fixed effects.

The effect of an immigrant householder's year of arrival on their homeownership probability followed the predicted trend: the greater the amount of time since an immigrant household head's arrival in the U.S., the greater the probability that they own their home. This proved to be particularly explanatorily powerful, even after controlling for age (which is closely related but not the same). Indeed, it was found that immigrants who arrived in the U.S. a few decades before the date of the survey (either 2006 or 2019) were predicted to have roughly the same probability of homeownership as, and perhaps even surpass, the group of all natives (on average and *ceteris paribus*) after adjusting for socioeconomic characteristics and metropolitan area fixed effects.

My investigation of immigrant-specific characteristics found that, as anticipated, an immigrant's citizenship status and linguistic isolation (which proxied for a household's proficiency in the English language) were significant predictors of homeownership as well. It was found that immigrant household heads who achieved citizenship were as likely as (if not more likely than) natives to own their homes in both 2006 and 2019, on average and *ceteris paribus,* while non-citizen immigrant household heads seemed to be at a severe disadvantage even after controlling for socioeconomic characteristics and metropolitan area fixed effects. The findings regarding linguistic isolation were similar, with non-linguistically isolated households approaching (but evidently not reaching) homeownership parity with natives in both years and linguistically isolated households having a substantially lower probability of homeownership.

To dispel any concerns that the coefficient estimates for these immigrant-specific variables might be capturing each other's effects, I ran an immigrant-only regression controlling for all of the immigrant-specific variables at once (in addition to the standard socioeconomic and metropolitan area controls). The results of this regression demonstrated that each of those immigrant-specific predictors were independently important, though it may have taken some of the significance out of some of the national origin effects.

Finally, I demonstrated the apparent predictive importance of ethnic enclaves, as proxied by Borjas' (2002) "exposure index," by running immigrant-only regressions for only those immigrants from the largest twenty countries of origin who lived in the largest twenty metropolitan areas in the sample. The coefficient on the exposure index variable was statistically significant for both 2006 and 2019. Thus, in line with the past literature on the subject, my research seems to support the idea that the presence of ethnic enclaves can help to raise the homeownership probability of immigrant households in the area.

7. Conclusion

In this paper, I hope to have shed some light on the state of immigrant homeownership in the United States and to have provided some evidence to suggest how it might be changing over time. On the whole, I have confirmed the importance of many of the factors that have traditionally been thought to determine immigrant homeownership in addition to highlighting the importance of several immigrant-specific features that do much to explain the gap between immigrant and native homeownership.

The policy implications of this research are not immediately obvious and depend, as always, on the goals of the authorities. If parity of homeownership between immigrants and natives is desired, it seems that providing easier paths to citizenship and providing opportunities for immigrants to become proficient in English might be a couple different ways of doing so. Though this paper did not directly touch on issues of discrimination, it seems that removing the influence of discrimination in the housing and loan markets should also help to close this gap. In addition, since immigrants evidently have a higher tendency to live in large urban areas than natives (New York and Los Angeles in particular), making those large cities more affordable (at least in terms of housing costs) would probably serve to narrow the native-immigrant homeownership gap. Furthermore, there is reason to think that the “paperwork burden” associated with homeownership is more difficult to surmount for immigrant households than native ones. As a result, one way of improving homeownership in the immigrant population would be to provide services to assist immigrant households in navigating the process of getting a mortgage and purchasing a home.

Though I do not necessarily endorse such policies, my results suggest that implementing a points-based immigration system that takes into account potential immigrants’ educational attainment, marital status, income in their country of origin, and other relevant socioeconomic characteristics that have been shown to influence the probability of homeownership would probably serve to raise immigrant homeownership. Similarly, screening immigrants based on their country of origin and admitting only those from countries likely to produce future homeowners might be another way of increasing the U.S. immigrant homeownership rate, if such a thing is a priority of policymakers (though again, I would not necessarily endorse such a policy because it would likely raise serious ethical questions).

However, there are some aspects of immigrant homeownership that likely fall outside the reach of policy. For instance, an immigrant household head’s year of immigration was found to be an important explanatory variable for immigrant households. Since this likely proxies for U.S.-specific skills that immigrant households acquire over their time in the country as well as their familiarity with the housing/mortgage markets, the wealth they accrue over time in the U.S., and potentially their credit histories, there is not much that can be done in terms of policy to help close the part of the gap that is due to the fact that immigrants have not spent all of their lives living in the U.S. (like most natives presumably have). It may also be that perhaps not all immigrants plan on staying in the U.S. for the rest of their lives and therefore have a more temporary view in mind. If this is so, then there is reason to expect a systematic tendency for immigrants to have a higher propensity to rent, all else equal. This, too, if it is true, is not something that policy could reasonably address, at least not by conventional means (though it seems like one possibility might be to use some kind of incentives to make sure that immigrants stay in the country—though, like before, I would not necessarily endorse such a policy).

Avenues for further research abound. This paper was designed to be rather far-reaching, but there are opportunities for additional investigation regarding the details of many of the facets of immigrant homeownership that were touched on here. For example, the issue of metropolitan area of residence and the influence of ethnic enclaves is something that might merit further attention. If a measure more direct than the exposure index could better get at the presence of ethnic enclaves, for example, it might be worth investigating that issue further. There may also be questions about whether controlling for metropolitan area is precise enough—perhaps looking at cities rather than full metropolitan areas would prove more insightful, for instance, if there are important distinctions between living in a larger metro area and living with an actual urban center that went unaddressed in this paper.

The interesting findings regarding country of origin also open up multiple possible avenues for future research. “Zooming in” on specific national origin groups—and in particular, the big ones—might be an interesting way of gleaning additional information about what makes a particular group “successful” in terms of homeownership in the U.S. and what does not seem to work.

I assumed throughout this research, for simplicity, that the socioeconomic characteristics and metropolitan area fixed effects would apply to immigrants and natives equally and in the same manner. This assumption is at least relatively plausible; it is not immediately clear that factors like income, marital status, the cost of living/owning a home in different cities, etc. would affect the probability of homeownership differently for natives than for immigrants. Still, I did not conduct any analyses to determine whether socioeconomic characteristics or metropolitan area of residence might affect the probability of immigrant homeownership differently than the probability for natives. Thus, it might be worth investigating which, if any, specific variables seem to affect the two groups differently.

The measure of homeownership used throughout this research was simply a binary outcome; I only looked in detail at the extensive margin of homeownership. Illuminating results might be gleaned from a study of homeownership at the intensive margin; perhaps the probability of owning multiple homes differs between immigrants and natives, or perhaps one group is more likely to have an active mortgage (or even a second mortgage) than the other. These are questions that could be investigated in further research.

Though my research intentionally investigated one year before and one year after the 2008-2009 financial crisis, I did not explicitly give much attention to the issue of whether that event might have affected the homeownership of natives differently than immigrants. My research provided preliminary evidence for thinking that the homeownership rate for natives declined over the period from 2006 to 2019 while the immigrant rate seemed to remain relatively constant, but I did not investigate the issue further. It is possible that this observation is at least partially related to that crisis. Future research could uncover the answers to that question.

Though it is probably too early to tell exactly how current events will affect the housing market in the years to come, it would certainly be interesting to see how the Covid-19 pandemic will end up affecting homeownership and, more specifically, the native-immigrant homeownership gap.

And finally, my paper has documented a rich set of estimates associated with the (theory-driven) determinants of homeownership while remaining silent with regard to the uncertainty of the estimates. One natural methodological extension of this research could consider a more flexible identification strategy that accounts for the entire *distributions* or the estimates—an extension that could be useful for policymaking.

Appendix: Additional Tables

Appendix Table A. Baseline regression, no immigrant-specific characteristics

	2006	2019
Socioeconomic characteristics		
Number of individuals in household	0.019***	0.012***
	(0.001)	(0.001)
Number of householder’s children in household	0.004***	0.009***
	(0.001)	(0.001)
Age	0.025***	0.024***
	(0.0001)	(0.0001)
Age squared	−0.0002***	−0.0001***
	(0.00000)	(0.00000)
Female	0.001	0.005***
	(0.001)	(0.001)
Married	0.111***	0.117***
	(0.001)	(0.001)
Black	−0.143***	−0.166***
	(0.001)	(0.001)
American Indian/Alaska Native	−0.069***	−0.040***
	(0.004)	(0.004)
Asian/Pacific Islander	−0.086***	−0.055***
	(0.002)	(0.002)
Hispanic/Latino	−0.106***	−0.100***
	(0.001)	(0.001)
log Income	0.218***	0.138***
	(0.001)	(0.001)
High school	0.058***	0.070***
	(0.001)	(0.001)
Some college	0.063***	0.080***
	(0.001)	(0.001)
Bachelor’s degree	0.070***	0.095***
	(0.001)	(0.002)
Advanced degree	0.044***	0.081***
	(0.002)	(0.002)
Employed or N/A	0.066***	0.041***
	(0.002)	(0.003)
Not in the labor force	0.063***	0.054***
	(0.002)	(0.003)

Appendix Table A, Continued

	2006	2019
Metropolitan area fixed effects		
Atlanta-Sandy Springs-Roswell, GA	0.013***	0.005*
	(0.003)	(0.003)
Baltimore-Columbia-Towson, MD	−0.024***	−0.017***
	(0.004)	(0.004)
Boston-Cambridge-Newton, MA-NH	−0.106***	−0.116***
	(0.003)	(0.003)
Chicago-Naperville-Elgin, IL-IN-WI	−0.018***	−0.024***
	(0.002)	(0.002)
Dallas-Fort Worth-Arlington, TX	−0.035***	−0.054***
	(0.003)	(0.002)
Denver-Aurora-Lakewood, CO	−0.014***	−0.036***
	(0.004)	(0.004)
Detroit-Warren-Dearborn, MI	0.034***	0.023***
	(0.003)	(0.003)
Houston-The Woodlands-Sugar Land, TX	−0.026***	−0.032***
	(0.003)	(0.003)
Los Angeles-Long Beach-Anaheim, CA	−0.161***	−0.173***
	(0.002)	(0.002)
Miami-Fort Lauderdale-West Palm Beach, FL	−0.007**	−0.041***
	(0.003)	(0.003)
New York-Newark-Jersey City, NY-NJ-PA	−0.169***	−0.156***
	(0.002)	(0.002)
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	−0.013***	−0.019***
	(0.003)	(0.003)
Phoenix-Mesa-Scottsdale, AZ	−0.011***	−0.032***
	(0.003)	(0.003)
Riverside-San Bernadino-Ontario, CA	−0.017***	−0.036***
	(0.003)	(0.003)
San Diego-Carlsbad, CA	−0.128***	−0.145***
	(0.004)	(0.004)
San Francisco-Oakland-Hayward, CA	−0.150***	−0.186***
	(0.003)	(0.003)
Seattle-Tacoma-Bellevue, WA	−0.076***	−0.088***
	(0.003)	(0.003)
St. Louis, MO-IL	0.019***	0.019***
	(0.004)	(0.004)
Tampa-St. Petersburg-Clearwater, FL	0.003	−0.011***
	(0.003)	(0.003)
Washington-Arlington-Alexandria, DC-VA-MD-WV	−0.065***	−0.064***
	(0.003)	(0.003)
Constant	−2.809***	−1.872***
	(0.011)	(0.007)
R^2	0.253	0.256
Number of observations	1,163,343	1,276,716

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are reported in parentheses. Regressions include all observations in the sample for each year. Before taking the log of income, households' incomes were transformed by shifting each household's income up by the amount of the absolute value of the lowest income (which in both years was a negative value). Since the 2006 households' incomes were shifted up by a different amount than the 2019 ones, the coefficients on the "log Income" variable are not directly comparable.

Appendix Table B. Logit regression model results

	2006	2019
Socioeconomic characteristics		
Number of individuals in household	0.089***	0.074***
	(0.004)	(0.003)
Number of householder’s children in household	0.038***	0.022***
	(0.005)	(0.004)
Age	0.137***	0.129***
	(0.001)	(0.001)
Age squared	−0.001***	−0.001***
	(0.00001)	(0.00001)
Female	−0.037***	−0.011**
	(0.005)	(0.005)
Married	0.675***	0.719***
	(0.006)	(0.005)
Black	−0.745***	−0.863***
	(0.008)	(0.007)
American Indian/Alaska Native	−0.387***	−0.228***
	(0.028)	(0.025)
Asian/Pacific Islander	−0.363***	−0.161***
	(0.014)	(0.012)
Hispanic/Latino	−0.429***	−0.423***
	(0.010)	(0.008)
log Income	1.877***	0.960***
	(0.009)	(0.004)
High school	0.280***	0.321***
	(0.008)	(0.009)
Some college	0.304***	0.392***
	(0.008)	(0.009)
Bachelor’s degree	0.374***	0.513***
	(0.010)	(0.010)
Advanced degree	0.250***	0.453***
	(0.011)	(0.010)
Employed or N/A	0.220***	0.124***
	(0.014)	(0.017)
Not in the labor force	0.313***	0.288***
	(0.015)	(0.017)

Appendix Table B, Continued

	2006	2019
Metropolitan area fixed effects		
Atlanta-Sandy Springs-Roswell, GA	0.095***	0.045**
	(0.021)	(0.019)
Baltimore-Columbia-Towson, MD	−0.191***	−0.103***
	(0.027)	(0.026)
Boston-Cambridge-Newton, MA-NH	−0.722***	−0.727***
	(0.020)	(0.019)
Chicago-Naperville-Elgin, IL-IN-WI	−0.114***	−0.139***
	(0.016)	(0.015)
Dallas-Fort Worth-Arlington, TX	−0.227***	−0.331***
	(0.018)	(0.016)
Denver-Aurora-Lakewood, CO	−0.099***	−0.253***
	(0.028)	(0.024)
Detroit-Warren-Dearborn, MI	0.259***	0.183***
	(0.024)	(0.023)
Houston-The Woodlands-Sugar Land, TX	−0.145***	−0.179***
	(0.020)	(0.018)
Los Angeles-Long Beach-Anaheim, CA	−0.980***	−1.000***
	(0.013)	(0.012)
Miami-Fort Lauderdale-West Palm Beach, FL	0.009	−0.185***
	(0.019)	(0.017)
New York-Newark-Jersey City, NY-NJ-PA	−1.058***	−0.921***
	(0.011)	(0.010)
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	−0.085***	−0.101***
	(0.020)	(0.019)
Phoenix-Mesa-Scottsdale, AZ	−0.071***	−0.206***
	(0.022)	(0.020)
Riverside-San Bernadino-Ontario, CA	−0.147***	−0.247***
	(0.024)	(0.022)
San Diego-Carlsbad, CA	−0.843***	−0.891***
	(0.024)	(0.023)
San Francisco-Oakland-Hayward, CA	−1.013***	−1.170***
	(0.020)	(0.019)
Seattle-Tacoma-Bellevue, WA	−0.529***	−0.583***
	(0.023)	(0.021)
St. Louis, MO-IL	0.152***	0.135***
	(0.029)	(0.027)
Tampa-St. Petersburg-Clearwater, FL	0.021	−0.072***
	(0.024)	(0.021)
Washington-Arlington-Alexandria, DC-VA-MD-WV	−0.471***	−0.414***
	(0.020)	(0.017)
Immigrant	−0.321***	−0.305***
	(0.009)	(0.008)
Constant	−25.890***	−15.069***
	(0.096)	(0.053)
Number of observations	1,163,343	1,276,716

* p < 0.10, ** p < 0.05, *** p < 0.01. Standard errors are reported in parentheses. Regressions include all observations in the sample for each year. Before taking the log of income, households' incomes were transformed by shifting each household's income up by the amount of the absolute value of the lowest income (which in both years was a negative value). Since the 2006 households' incomes were shifted up by a different amount than the 2019 ones, the coefficients on the "log Income" variable are not directly comparable.

References

Aaronson, D. (2000). A Note on the Benefits of Homeownership. *Journal of Urban Economics*, *47*(3), 356-369.

Amuedo-Dorantes, C., & Mundra, K. (2013). Immigrant Homeownership and Immigration Status: Evidence from Spain. *Review of International Economics*, *21*(2), 204-218.

Barker, D., & Miller, E. (2009). Homeownership and Child Welfare. *Real Estate Economics*, *37*(2), 279-303.

Boehm, T. P., & Schlottmann, A. M. (1999). Does Homeownership by Parents Have an Economic Impact on their Children? *Journal of Housing Economics*, *8*(3), 217-232.

Borjas, G. J. (1985). Assimilation, Changes in Cohort Quality, and the Earnings of Immigrants. *Journal of Labor Economics*, *3*(4), 463-489.

Borjas, G. J. (1994). The Economics of Immigration. *Journal of Economic Literature*, *32*(4), 1667-1717.

Borjas, G. J. (2002). Homeownership in the Immigrant Population. *Journal of Urban Economics*, *52*(3), 448-476.

Budiman, A. (2020, September 22). Key findings about U.S. immigrants. Retrieved September 21, 2021, from https://www.pewresearch.org/fact-tank/2020/08/20/key-findings-about-u-s-immigrants/.

Carliner, G. (1974). Determinants of Home Ownership. *Land Economics*, *50*(2), 109-119.

Chiswick, B. R. (1978). The Effect of Americanization on the Earnings of Foreign-Born Men. *Journal of Political Economy*, *86*(5), 897-921.

Constant, A. F., Roberts, R., & Zimmermann, K. F. (2009). Ethnic Identity and Immigrant Homeownership. *Urban Studies*, *46*(9), 1879-1898.

Coulson, N. E. (1999). Why Are Hispanic- and Asian-American Homeownership Rates So Low?: Immigration and Other Factors. *Journal of Urban Economics*, *45*(2), 209-227.

DeSilva, S., & Elmelech, Y. (2012). Housing Inequality in the United States: Explaining the White-Minority Disparities in Homeownership. *Housing Studies*, *27*(1), 1-26.

Freddie Mac Research. (2019, June). Profile of Today's Renter & Homeowner. Freddie Mac. Retrieved January 27, 2022, from http://www.freddiemac.com/fmac-resources/research/pdf/Freddie_Mac_Profile_of_Todays_Renter_and_Homeowner.pdf

Friedman, N. (2021, December 14). Millennials Are Supercharging the Housing Market. *The Wall Street Journal*. Retrieved January 27, 2022, from https://www.wsj.com/articles/millennials-are-supercharging-the-housing-market-11639496815

Green, R. K., & White, M. J. (1997). Measuring the Benefits of Homeowning: Effects on Children. *Journal of urban economics*, *41*(3), 441-461.

Harkness, J., & Newman, S. (2003). Differential Effects of Homeownership on Children from Higher- and Lower-Income Families. *Journal of Housing Research*, *14*(1), 1–19. http://www.jstor.org/stable/44944772

Haurin, D. R., Parcel, T. L., & Haurin, R. J. (2002). Does Homeownership Affect Child Outcomes? *Real Estate Economics*, *30*(4), 635-666.

Kauppinen, T. M., & Vilkama, K. (2016). Entry to Homeownership Among Immigrants: A Decomposition of Factors Contributing to the Gap with Native-Born Residents. *Housing Studies*, *31*(4), 463-488.

Kuebler, M., & Rugh, J. S. (2013). New Evidence on Racial and Ethnic Disparities in Homeownership in the United States from 2001 to 2010. *Social Science Research*, *42*(5), 1357-1374.

McCabe, B. J. (2018). Why Buy a Home? Race, Ethnicity, and Homeownership Preferences in the United States. *Sociology of Race and Ethnicity*, *4*(4), 452-472.

Megbolugbe, I. F., Marks, A. P., & Schwartz, M. B. (1991). The Economic Theory of Housing Demand: A Critical Review. *The Journal of Real Estate Research*, *6*(3), 381–393.

Mundra, K. (2020). Immigrant and Minority Homeownership Experience: Evidence from the 2009 American Housing Survey. *Eastern Economic Journal*, *46*(1), 53-81.

Mundra, K., & Uwaifo Oyelere, R. (2017). Determinants of Homeownership Among Immigrants: Changes During the Great Recession and Beyond. *International Migration Review*.

Myers, D., Lee, H., & Simmons, P. A. (2020). Cohort Insights into Recovery of Millennial Homeownership After the Great Recession. *Journal of Housing Economics*, *47*, 101619.

Myers, D., Megbolugbe, I., & Lee, S. (1998). Cohort Estimation of Homeownership Attainment Among Native-Born and Immigrant Populations. *Journal of Housing Research*, *9*(2), 237-269.

Painter, G., Yang, L., & Yu, Z. (2004). Homeownership Determinants for Chinese Americans: Assimilation, Ethnic Concentration and Nativity. *Real Estate Economics*, *32*(3), 509-539.

Painter, G., & Yu, Z. (2014). Caught in the Housing Bubble: Immigrants' Housing Outcomes in Traditional Gateways and Newly Emerging Destinations. *Urban Studies*, *51*(4), 781-809.

Rexrode, C. (2019, July 27). Financial Crisis Yields a Generation of Renters. *The Wall Street Journal*. Retrieved January 27, 2022, from https://www.wsj.com/articles/financial-crisis-yields-a-generation-of-renters-11564228800?mod=article_inline

Ruggles, S., Flood, S., Goeken, R., Grover, J., Meyer, E., Pacas, J., & Sobek, M. IPUMS USA: Version 10.0 [dataset]. Minneapolis, MN: IPUMS, 2020. https://doi.org/10.18128/D010.V10.0

Sinning, M. (2010). Homeownership and Economic Performance of Immigrants in Germany. *Urban Studies*, *47*(2), 387-409.

World Bank. (2019). Birth rate, crude (per 1,000 people) - United States. Retrieved March 14, 2022, from https://data.worldbank.org/indicator/SP.DYN.CBRT.IN?locations=US