Racial Dynamics of Federal Property Buyouts in Flood-Prone Areas*

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Abstract

Recent climate projections forecast significant increases in flood risks, and the greatest increases are anticipated to be in communities of color. The use of managed retreats, or "buyouts," of flood-prone properties as an adaptation response is also likely to grow. This paper investigates the equity implications of managed retreat by analyzing the role of race and ethnicity in buyout bargaining outcomes and how those outcomes affect longer-run neighborhood change. To do this, we combine nationwide administrative data on federal property acquisitions and housing sales transactions with a database tracking individual movement over time. We then estimate the discount in buyout payments relative to a property's fair market value, how the payment received affects where households relocate, and whether these impacts differ by race. We find that the buyout compensation received by families of color is around 8-10 percent lower than that received by white families. Moreover, these price discounts detract from individual wealth and the quality of the neighborhood to which families relocate. Our work highlights how government policy, aimed to address increasing climate impacts, may exacerbate the burden of climate change on vulnerable communities.

JEL Codes: D30, D63, Q50, R23

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1 Introduction

There is growing concern over flood risk. Rising temperatures from climate change cause thermal expansion and loss of ice mass which lead to global sea level rise (SLR) and increased coastal flooding (Wing et al., 2022). Recent projections estimate that 4 to 13 million Americans will be at risk from SLR by 2100 (Hauer et al., 2016). Increases in the frequency and magnitude of extreme precipitation events are also estimated to put an additional 7.8 to 12 million people at risk of flooding in the coterminous U.S. (Swain et al., 2020). A recent paper estimates that the average annualized flood loss as of 2020 is $32.1 billion; losses are expected to increase by 26.4 percent, and the greatest increases are expected to be in communities of color (Wing et al., 2022). There are various strategies to adapt to this increased risk, ranging from ex ante policies such as flood-proofing infrastructure and risk-based flood insurance pricing to ex post policies of disaster assistance. Managed retreats, or property "buyouts," represent one such adaptation strategy that has mostly been used as an ex post approach in a post-disaster context. Retreat will be an unavoidable adaptation option for many communities going forward (USGCRP, 2018; Kousky, 2014b; Carey, 2020).

In a buyout program, owners of eligible properties are offered their property's pre-disaster, fair-market value to relocate from a hazard-prone area with the aim to reduce future flood losses. The primary source of federal funding for buyouts in the US is the FEMA Hazard Mitigation Grant Program, which authorizes funding for property acquisitions after a Presidentally Declared Disaster (PDD) (Kousky, 2014b). From 1989 to 2017, FEMA funded 43,633 buyouts of flood-prone properties across 1,148 counties in 44 states (Mach et al., 2019). Individuals cannot directly apply for funding; rather, the state or local government must submit an application. In doing so, the applicant must also conduct a benefit-cost analysis to show that the future benefits of acquiring the proposed set of properties exceeds the costs. If the application is successful and owners agree to sell, then the property is demolished (or relocated, in some cases) and the land is maintained as open space.[1]

While FEMA states that buyouts are strictly voluntary (FEMA 2007), evidence from case studies suggests that this is often not the case in practice. In a survey of four cities with buyout programs, approximately one third of the participants stated that they felt forced into participation (De Vries and Fraser, 2012). Moreover, work across various disciplines has found that buyouts are more likely to be administered in areas of low socioeconomic status (Mach et

[1] While there are deed restrictions on post-buyout infrastructure for the FEMA buyout program, this is not the case with other programs such as the US Housing and Urban Development (HUD) Community Development Block Grants.

al., 2019; Elliott et al., 2020) and raise questions of social equity (Siders, 2019; Dineva et al., 2021). Two program features, in particular, are likely to place disproportionate burden on low SES groups: the substantial damage declaration and temporary building moratoria (De Vries and Fraser, 2012; Binder and Greer, 2016). The substantial damage declaration states that if the cost of repair is over 50 percent of a home's pre-flood value, then the homeowner is not legally allowed to rebuild unless they can flood-proof their home. This is intended to increase the overall net benefits of the program. However, if low-valued homes are more likely to exceed the damage threshold and wealthy owners are more likely to afford repairs, then this means that low SES individuals and communities of higher vulnerability would be more likely to be the target of buyout programs. Temporary re-building moratoria further increase the chance that owners accept buyout offers because it prevents property repairs from being made so that households cannot return to their homes.

In this paper, we examine two research questions. First, we examine the role of race and ethnicity in buyout bargaining outcomes (i.e., buyout compensations). Second, we investigate longer-run impacts of the program in terms of where recipients of FEMA buyout funds relocate, how the payment received affects that relocation decision, and whether these impacts differ by race. Our analysis is performed in two stages. First, we match FEMA buyout acquisitions to nationwide administrative records on property sales based on exact address. From this, we recover the buyout price that owners received and compare that to the fair-market value (FMV) that they should have received as predicted from non-buyout properties that sold within the same block group in that year. Our prediction of FMVs is based on estimating county-specific hedonic models with high dimensional (i.e., block group) spatial fixed effects to control for local variation in determinants of housing prices. We use probabilistic matching based on surname and county of residence (Imai and Khanna, 2016) to identify the owner's race, and then estimate a simple regression to recover how the price discount systematically varies by race. Second, we match the participants in our buyout sample to individuals in a database that tracks address, wealth, and income for over 292 million people over time in the U.S.. Matching is performed based on the address of the participant at or after the fiscal year of the buyout program. This allows us to follow where individuals relocate after participating in the buyout and how their wealth and income changes over time.

We provide novel evidence on the impact of managed retreat on short- and longer-term well-being and how these impacts vary by race. Literature to date focuses on where buyouts occur and who accepts buyouts (Tate et al., 2016; Mach et al., 2019; McGhee et al., 2020), but few have examined outcomes such as the buyout compensation and where people relocate. Among case studies that have studied outcomes, most survey program satisfaction, but buyout compensation is an important outcome of this process since housing is a large source of wealth for many households. Previous work has also been unable to answer a key question that we are equipped to answer: have these programs effectively reduced future flood damage by relocating households to areas of lower flood risk? Beyond environmental risk, recent work has also highlighted the important role of neighborhoods on well-being and social mobility (Chetty et al., 2016; Chetty and Hendren, 2018a,b; Chyn and Katz, 2021; Deryugina and Molitor, 2021). If compensation is disproportionately incomplete and if managed retreat causes the vulnerable to relocate to lower quality neighborhoods with fewer opportunities, then this process perpetuates gaps in well-being.

In preliminary analysis, we find that the buyout compensation received by minority families is approximately 8-10 percent lower (relative to their property's fair market price) than that received by white families. These price discounts detract from individual wealth and the quality of the neighborhood to which families relocate. Receiving a $10,000 discount in one's buyout payment disproportionately increases the percent of households under the poverty line and single parent households in the destination location (relative to origin) neighborhood by, respectively, 4 and 3 percent for Black relative to white families. For Black families, the same amount of discount decreases percent employed in skilled occupations in the destination location by 1.5 percent, on average.

Our work adds to the body of research that evaluates the damages from climate change and effectiveness of adaptation strategies (Kousky, 2014a). Indirectly related, is the work that documents the various impacts of disasters, including on labor markets (Vigdor, 2007; McIntosh, 2008), academic performance (Sacerdote, 2012), health outcomes (Currie and Rossin-Slater, 2013), debt and credit (Deryugina et al., 2018; Gallagher and Hartley, 2017; Billings et al., 2022), and displacement and migration (Sheldon and Zhan, 2021). Our focus on equity in managed retreats connects our work to the environmental and climate justice literature (Banzhaf et al., 2019). Current work already expects that future climate damages will be more heavily felt by communities of color. We highlight how government policy, aimed to address those climate impacts, may exacerbate the burden of climate change on vulnerable communities. As the need for managed retreat increases and buyouts shift from being a reactive to preemptive adaptation strategy, careful attention to both the overall and distributive impacts adaptation policy is needed.

Section 2 first provides some institutional details about the FEMA buyout program based on

FEMA guidance on hazard mitigation assistance (FEMA, 2015). We present our data sources and construction in Section 3. Section 4 presents methods. We discuss preliminary results in Section 5. Section 7 concludes.

2 Institutional Details

2.1 FEMA Buyout Program

The basic process of an acquisition project is such that the community purchases a flood-prone structure from a willing seller and then demolishes the property or, in some cases, relocates it to a location outside the floodplain. A property is generally eligible if it contains a structure that may or may not have been damaged or destroyed as a result of a hazard event. The Hazard Mitigation Grant Program (HMGP), authorized by Section 404 of the Stafford Act, is one of the primary sources of federal funding for property acquisitions in the US. Funding cannot be directly requested by individuals or individual organizations and instead must be requested by the Governor or equivalent after a Presidential major disaster declaration (PDD). Eligible applicants include the emergency management agency of the state, territories, and federally-recognized tribes. These applicants can solicit sub-applicants, which can include local government, communities, and certain private non-profits (e.g., a conservation organization).[2] Individual property owners are responsible for notifying the sub-applicant of their participation interest.

Applications undergo a technical review, which evaluates project cost effectiveness, feasibility, and compliance with existing laws (e.g., considerations if a project impacts endangered species or historic resources). Mitigation measures are required to be cost effective, which is typically demonstrated by showing that the benefit-cost ratio, comparing the total annualized project benefits and costs, exceeds one.[3] In 2011, FEMA began requiring the consideration of climate change into its programs[4] and has begun funding projects that incorporate sea level rise (SLR) estimates. Applicants must submit all HMGP sub-applications to FEMA within 12 months of the date of the PDD. FEMA then selects eligible sub-applications based on state or federal program priorities. FEMA establishes the HMGP funding ceiling for each disaster at 12 months after the PDD, where the maximum amount of HMGP funding available is calculated using a "sliding scale" formula based on a percentage of the estimated total Federal assistance authorized.[5]

[2] Proposed projects of sub-applicants sited within an SFHA are eligible only if the jurisdiction participates in the NFIP. NFIP participation is not required for HMGP projects located outside of the SFHA.

[3] The benefit-cost analysis is usually performed using a software approved by the state emergency authority.

[4] See FEMA's Climate Change Adaptation Policy Statement (2011-OPPA-01)

[5] The formula provides for up to 15 percent of the first $2 billion of estimated aggregate amounts of disaster

Funding requires a non-federal cost-share of 25 percent for mitigation activities.[6]

If a project is approved, applicants are referred to as 'recipients' and sub-applicants become 'sub-recipients.' Sub-recipients are often responsible for implementing property acquisitions, which includes clearing the property title, obtaining the statement of voluntary participation, and providing mitigation offers. A title search is conducted to ensure the property owner is the sole and actual titleholder of the property. Property owners are then given a mitigation (purchase) offer that is based on the market value of their home, which is often the pre-disaster market value of the property. The sub-recipient notifies the appraised value of the property (and method used to determine the value) in writing using a Statement of Voluntary Participation.

The appraisal must be conducted by an appraiser in accordance with the Uniform Standards of Professional Appraisal Practice (UCR) and State laws and requirements. Owners who wish to dispute the amount of the purchase offer can do so using a process laid out by the sub-recipient. If the owner agrees to participate, then they sign the statement. Although participation is voluntary for property owners, that is not the case for tenants and owners of mobile homes who rent homepads.[7] The purchase offer is subject to deductions and additions. Federal funding received for disaster aid, including insurance payouts that are not used for repairing the property, is deducted from the purchase price to prevent Duplication of Benefits (Siders and Gerber-Chavez, 2021). Additions to the purchase price could occur if the offer is demonstrated to be less than the amount the owner must pay to relocate to a comparable replacement dwelling in a non-hazard-prone site in the same community. The supplemental payment may be up to $31,000.

Upon purchase, the property is deed-restricted in perpetuity to be maintained as open space (or some alternative land use that can service floodplain functions), where recipients and sub-recipients are responsible for future enforcement of proper land use. Examples of allowable land uses include parks for outdoor recreational activities, wetlands management, nature reserves, cultivation, grazing, and camping.

assistance, up to 10 percent for amounts between $2 billion and $10 billion, and up to 7.5 percent for amounts between $10 billion and $35.333 billion. The eligible assistance is up to 20 percent for estimated aggregate amounts of disaster assistance, up to $35.333 billion, excluding administrative costs (Title 44 of the CFR).

[6] Non-federal cost share can be cash, in-kind services, or materials, subject to verification. No cost-sharing is required for management costs.

[7] The Uniform Relocation Assistance and Real Property Acquisition Policies Act of 1970 (URA) provides some assistance to displaced tenants for moving expenses and increases in rent and utility costs with the relocation.

2.2 Overall Cost Effectiveness, Unequal Burdens

The intended goal of acquisitions is to mitigate future damage from disasters such as flood risk. However, important features of the program are likely to have placed more burden on the socially vulnerable. The cost-effectiveness program requirement, along with its several exceptions, make low-value homes a target for buyout programs. Conditional on having similar current and future flood risks, acquisitions of lower-valued homes yield higher benefit-cost ratios in terms of preventing future injury or loss of life and displacement costs. FEMA also has pre-calculated benefits for the acquisition of properties in SFHAs to expedite the BCA process: As long as the cost of acquisition is less than these pre-calculated benefits, then the applicant does not need to conduct a BCA to justify the project's cost-effectiveness.[8] There is thus lower administrative burden associated with showing the cost-effectiveness of acquiring low-valued homes.

Being identified as a cost-effective acquisition in and of itself is not necessarily a problem. However, paired with highly motivated planners to increase the efficiency of a program through broad compliance (BenDor et al., 2020), this has often placed undue pressure on communities to participate. A survey of four cities with buyout programs found one third of the participants felt forced into participation (De Vries and Fraser, 2012). If participation is not optional, then this reduces one's ability to negotiate a fair price.

Compounding these issues are the substantial damage waiver and temporary rebuilding moratoria (De Vries and Fraser, 2012). A property is declared as substantially damaged if the "the cost of restoring the building to its before-damaged condition would equal or exceed 50 percent of the market value of the building before the damage occurred." Structures that are declared substantially damaged and those located in a rivervine Special Flood Hazard Area (SFHA) are automatically considered cost effective and are targets for acquisition.[9] Importantly, the homeowner is not legally allowed to rebuild if their home is declared as substantially damaged unless they can floodproof their home. With lower-value homes being more likely to exceed the damage threshold and low-income owners less likely to afford repairs, the option to stay becomes less viable for low SES property owners. Even if the owners decides to rebuild, this may be prevented by temporary rebuilding moratoria in the aftermath of a disaster, which further detracts from a property owner's ability to resist participation.

Many areas with low home values also coincide with areas of high social vulnerability and low social capital. Social capital disparities can affect the ability of communities to access needed

[8] The pre-calculated benefit amount for acquisitions in an SFHA is $323,000 (FEMA, 2022).

[9] A certification is required that these conditions are met.

expertise for appraisal negotiations. They can also interact with specific program features to directly reduce compensation for vulnerable populations. For example, while repair assistance that has been used for its intended purpose is generally not deducted from the purchase price, property owners must provide documentation (e.g., verify with receipts that the resources were expended on repairs or cleanup), otherwise it is considered a Duplication of Benefits and subtracted from the payment. Additions to the purchase price require demonstrating that the purchase price is insufficient to relocate to a comparable replacement dwelling. Social capital disparities may translate to lack of knowledge regarding proper documentation to minimize deductions or maximize additions to purchase offers. Rebuilding moratoria, if established, further prevent individuals from obtaining the documentation required to minimize deductions to payments by preventing re-building.

3 Data

3.1 Data Sources

Our work draws on four main data sources: (1) data on FEMA buyout transactions, (2) property sales transactions data from Corelogic, Inc., (3) data tracking movements of buyout participants from InfoUSA, Inc., and (4) block group level neighborhood characteristics from the U.S. Census American Community Survey (ACS) 5-year estimates.

FEMA buyout data were obtained by National Public Radio through a Freedom of Information Act request. The data include 41,004 buyouts across 49 states and 1,162 counties between 1989 and 2017. These data include the address of the buyout property, fiscal year of the buyout program, owner name, price paid, owner occupancy type, and house structure. Nationwide property sales data come from Corelogic, Inc. These data provide property attributes (e.g., address, age, number of bathrooms, square footage, etc.) as recorded from tax assessments for over 149 million parcels and sales and refinance transaction information (e.g., sale date, sale amount, and buyer and seller names) from over 575 million deed transactions.

Next, we track individual movement over time using InfoUSA, Inc. This is a consumer database that follows 120 million households and 292 million individuals between 2006 and 2020. Information from this database is constructed using 29 billion records from 100 sources, such as census statistics, billing statements, telephone directory listings and mail order buyers/magazine subscriptions. In addition to individual/household address, these data include characteristics of the individual/household such as race/ethnicity, family structure, renter/owner status, and estimated household income and wealth. Estimated wealth is based on infoUSA's WealthFinder Score. This is calculated by first assigning individuals to one of 20 rank-ordered net-worth categories based on a set of wealth indicators,[10] and then setting the individual's net worth as the median value, recorded in $1,000's, in that group. The range of estimated wealth after removing renters is $293,000 to $6.5 million.

Finally, we use ACS block group characteristics (e.g., percentages of those living in poverty, single parent households, educational attainment) to characterize how an individual's neighborhood changes over time. Since the ACS 5-year estimates are collected over a five-year period, we merge in neighborhood characteristics based on the year that corresponds to the mid-point of the period.

3.2 Data Construction

Data construction follows three main steps. First, we identify the transaction in the property sales data that corresponds to each buyout property. This allows us to recover the actual buyout price, date of sale, and owner information.[11] Next, we identify the race of the owner using probabilistic matching (Imai and Khanna, 2016), which is based on the owner's surname and state and county of residence. Finally, we track where the individual moves after being bought out. This is done by identifying the individual/family in the InfoUSA data based on the address of the buyout property and the fiscal year of the buyout program and then following all recorded individual movements afterwards. Addresses (before and after buyouts are administered) are geocoded to the census block group; we describe neighborhoods by merging block group data from the ACS. Because matches are imperfect, we are unable to recover information for all buyout properties. We detail the matching process and result below.

We first identify the *parcels* in the Corelogic data that are associated with the buyout properties based on address information. Once we identify the parcel in Corelogic, we then identify the sales transaction corresponding with the buyout transaction, which is taken as the first sales transaction during or after the fiscal year of the buyout project associated with the acquisition. There were 41,004 properties in the buyout data. After removing non-residential, non-primary, manufactured homes, we are left with 34,441 properties.[12]

Of these buyout properties, we matched 17,204 (50%) in the Corelogic data based on street

[10] Variables used to estimate net work include census data and proprietary consumer data such as income, investment activity, and philanthropic behavior (English et al., 2013).

[11] Buyout prices and owner names from the NPR FOIA data are frequently missing.

[12] We remove mobile homes and those that are not primary residences since the property owner is different from the resident.

number, name, ZIP code, city, and county FIPS code information.[13] We lose some additional buyouts when trying to identify the sales transaction. This leaves 13,475 buyout properties that are matched to housing transactions.[14]

We next recover the race of the seller in the transaction. This is done using probabilistic matching developed by Imai and Khanna (2016), which predicts individual-level ethnicity from geocoded voter registration records and Census Bureau's Surname List.[15] Specifically, we use the seller's last name, state, and county to predict the probability that an individual's race/ethnicity is white, Black, Hispanic, or some other race. The race/ethnicity of the owner involved in the property acquisition is taken as the category with the highest probability. Of the 13,475 matched properties, we recover race for 7,182, or about 53% of the buyout properties matched to sales transactions, using the name matching method based on housing transactions and InfoUSA surnames and voter registration records. Last, of the (7,182) buyout properties with race information, some are missing transactions prices. Because the buyout data have prices paid for a subset of the properties, we recover prices from the buyout data, when possible. We trim the top and bottom 1 percent of the price distribution to remove outliers (likely driven by recording errors or multi-unit dwellings). This leaves us with a final sample size of 5,948 matched buyout properties with both information on sales price and race.

Finally, we track wealth and movement over time by identifying the individual involved in the buyout transaction in the InfoUSA database and then following any subsequent moves that the individual makes. This matching is done based on the property address of the owner that is recorded at the time of the buyout program. Since the InfoUSA data are only available from 2006 to 2020, we will only be able to track wealth accumulation and movement for individuals participating in the more recent buyout programs.

Table 8 presents average block group-level characteristics in the year 2010 for the full sample of buyouts (columns 1-2) and broken down by whether the buyout could be matched to Corelogic (columns 3-4), matched to Corelogic and had race prediction (columns 5-6), or matched to Corelogic and InfoUSA (columns 7-8). For each subsample, we provide the t-statistic that tests whether the difference between the full sample and subsample mean is statistically different from zero. The sample of Corelogic matches is generally comparable to the full sample in terms

[13] Of the matched properties, properties (or 55%) matched exactly on street number, name, ZIP code, city, and county FIPS code. Another 35% matched exactly on street number and street name, and two of three pieces of address information: ZIP, city, and county FIPS code. The remaining 10% matched exactly on street number and street name, and either ZIP, city, or county FIPS code.

[14] In some cases, buyout properties are matched to the same property in Corelogic. These are dropped.

[15] Matching is performed using the WRU package in R.

of neighborhood characteristics, but is slightly more diverse (lower population share that is white), perhaps due to better Corelogic address information in urban areas. Neighborhood and population characteristics are also comparable to the full sample after probablistic matching to recover race. The sample that is matched to infoUSA is generally better off in terms of neighborhood characteristics such as poverty, single parent, education, and home ownership. Aside from the process to match buyout properties, it will also be important to understand selection into buyout, a point to which we return when we discuss our findings.

4 Methods

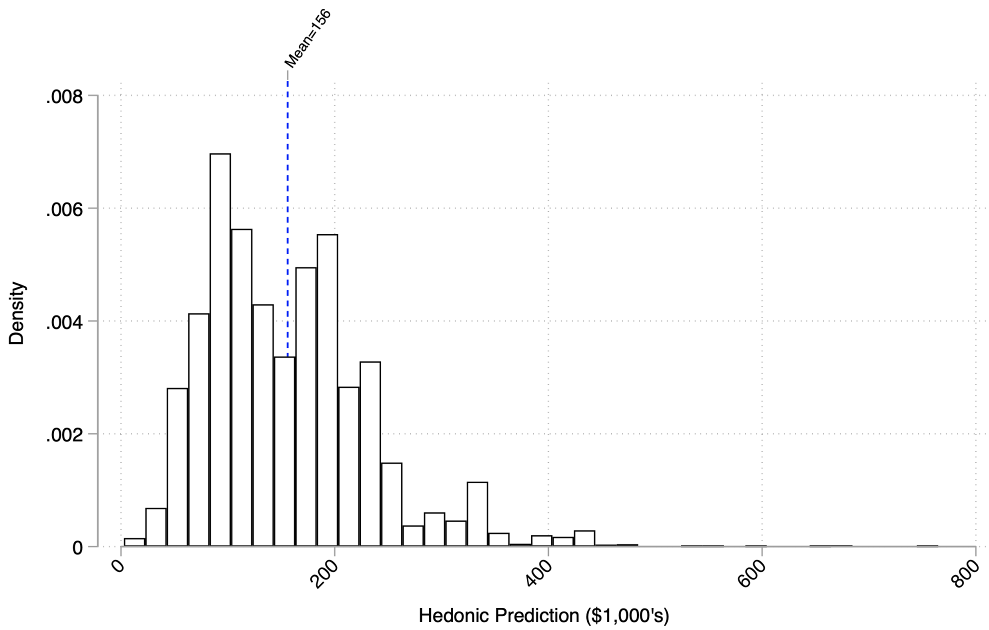
4.1 Price Prediction and Discrepancy by Race

We estimate a hedonic model using *non-buyout* properties to recover a pre-disaster, fair-market value (FMV) for each buyout property. A hedonic model could simply predict the FMV based on a house's structural characteristics. However, if, due to income or historical factors, minorities tend to live in low amenity areas with lower value housing, then ignoring neighborhood characteristics would cause us to overstate the market value of buyout homes for minorities and the discount in price that this group receives. To mitigate this, we separate estimation by county and control for block group-by-year fixed effects. For a house j in block group b of county c at time t, we estimate the following hedonic model, which we refer to as the 'prediction model', using all non-buyout houses in county c:

$$P_{j,b,c,t} = \alpha_{0,c} + \alpha_{1,c} X_{jt} + \eta_{b,c,t} + \epsilon_{j,b,c,t} \quad \forall\ j \notin \text{buyouts in county } c \tag{1}$$

The (county-specific) parameters estimated from the hedonic prediction model are used to predict the FMV of buyout properties located in the corresponding county. The set of property characteristics include living square footage, total baths, land square footage, number of bedrooms, age, and indicators for single family, condo, apartment, new construction, and mobile home. Because county assessors may differ in the set of house characteristics that they record, there are cases where certain characteristics are mostly missing for a particular county. For houses with missing values on characteristics, a zero is imputed and we create a separate dummy variable for whether the value is missing. The sample of non-buyout properties used for the prediction is cleaned by removing non-arms length transactions, those that are missing a transaction date, and those that are missing or have a zero sales price; we also trim the top and bottom percent

Figure 1: Hedonic Prediction



of the price distribution in each state. Figure 3 presents the distribution of hedonic estimates.

With the predicted FMV of each buyout property, we calculate the price discrepancy as a percent of the predicted price to recover the percent discount. We then estimate whether the buyout discount systematically varies based on the race of the owner. Specifically, we estimate the following model:

$$\frac{P_{k,t} - \hat{P}_{k,t}}{\hat{P}_{k,t}} = \beta_0 + \beta_1 Black_i + \beta_2 Hispanic_i + \beta_3 Other_i + \gamma_t + \gamma_s + \epsilon_{i,t} \quad \forall\, k \in buyouts \qquad (2)$$

where $P_{k,t}$ represents the actual buyout price of house k, $\hat{P}_{k,t}$ represents the hedonic prediction, and $Black_i$, $Hispanic_i$, and $Other_i$ are indicators for race (the omitted group for comparison is white owners). We control for unobserved differences across state-level buyout programs using state fixed effects and unobserved fluctuations over time with year fixed effects. We refer to this specification as the 'price discount model'.

We augment this baseline method to estimate racial buyout price discrepancies in a number of ways to understand the source of these discrepancies, e.g., if they result from the housing market or the buyout process. We evaluate these issues after presenting the main results on buyout discounts in section 5.

4.2 Long-term Impacts of Buyout Discounts

We follow on our analysis of price discounts to examine the longer-term effects on buyout participants. We do this by exploiting data tracking individual migration and wealth to evaluate wealth accumulation and neighborhood change. Let $W_{i,t}$ represent the estimated wealth of individual i at time t. We first assess how individual wealth changes after participating in the buyout process. Specifically, we estimate

$$log(W_{i,t}) = \beta_0 + \beta_1 Post_{i,t} + \gamma_t + \eta_i + \epsilon_{i,t} \tag{3}$$

where $Post_{i,t}$ is an indicator equal to 1 if the individual has relocated from the buyout property by time t and 0 if time t is before the fiscal year of the buyout program; γ_t are year fixed effects; η_i is an individual fixed effect. To further assess whether the buyout discount has a direct impact on wealth, we additionally interact the post-buyout indicator with the amount of the buyout discount:

$$log(W_{i,t}) = \beta_0 + \beta_1 Post_{i,t} + \beta_2 Post_{i,t} \times Discount_i + \gamma_t + \eta_i + \epsilon_{i,t} \tag{4}$$

The discount is defined as the hedonic prediction minus the actual price. A negative estimate on the parameter β_2 would suggest that larger price discounts are associated with larger declines in wealth after a family moves.

The specification above assesses evidence on the impact of buyout discounts on wealth. If Black and Hispanic owners systematically receive lower buyout prices (relative to the their homes' FMVs), then the buyout program is likely to have a disproportionately larger impact on wealth for minorities. To test for this directly, we estimate

$$log(W_{i,t}) = \beta_0 + \beta_1 Post_{i,t} + \beta_2 Race_i + \beta_3 Post_{i,t} \times Race_i + \gamma_t + \eta_i + \epsilon_{i,t} \tag{5}$$

$Race_i$ is a race indicator (e.g., $Black_i$ or $Hispanic_i$), where the omitted cateogory is white; η_i represents an individual-specific fixed effect. The coefficient of interest, β_3, returns the differential change in wealth for the Black or Hispanic group relative to the white group after participating in the buyout.

We can also examine whether the impact of discounts have a higher disproportionate wealth impact on minorities:

$$
\begin{aligned}
log(W_{i,t}) = \beta_0 + \beta_1 Post_{i,t} + \beta_2 Race_i + \beta_3 Post_{i,t} \times Race_i \\
+ \beta_4 Post_{i,t} \times Discount_i + \beta_5 Post_{i,t} \times Race_i \times Discount_i + \gamma_t + \eta_i + \epsilon_{i,t}
\end{aligned} \tag{6}
$$

If the parameter β_5 is negative, then this suggests that the same dollar value of price discount has a bigger (negative) impact on wealth for minorities than for whites.

In addition to wealth, we estimate the above models for income and various neighborhood characteristics that represent social vulnerability. Neighborhood characteristics (in percentages) include households below the poverty line, single parent households, those employed in skilled occupations, and those with less than a high school education. We also measure annual, block group level air pollution (RSEI Index) at each residence.

5 Results

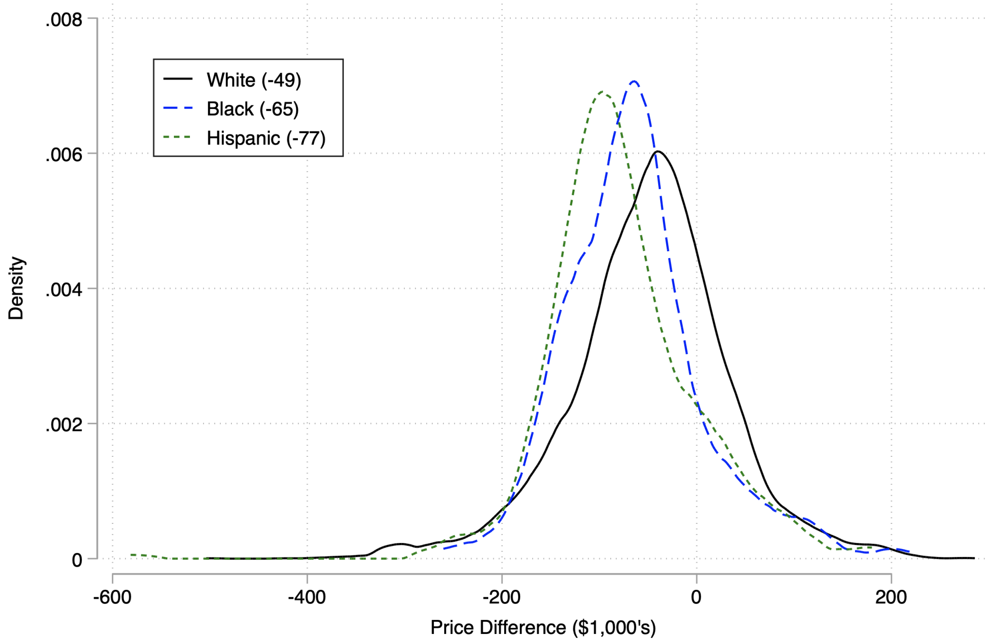
5.1 Price Discounts by Race

Figure 2 presents kernel density plots of the price discrepancies for white, Black, and Hispanic owners. The figure makes clear that, on average, Black and Hispanic owners receive a greater buyout discount on their property (relative to the property's FMV) compared to white owners. Table 2 shows the average price discount by race: white, Black, and Hispanic owners respectively receive an average discount of approximately \$49,000, \$63,000, and \$78,000. Table 3 presents the baseline price discrepancies as a percentage as estimated from equation 2. The column headers in Panel A indicates the spatial fixed effects used in the hedonic prediction to construct the buyout discount (tract, block group, and tract- or block group- specific time trends). All specifications include state and year of sale fixed effects.

We find that Black and Hispanic owners receive a buyout discount compared to white owners. This effect is persistent regardless of the specification used for the hedonic prediction. In our preferred specification (column 4), which relies on a hedonic prediction using sales of non-buyout properties in the same block group and sold during the same year as the buyout property, we find that Black owners receive a price discount that is 9.7 percentage points lower than white owners. The relative discount for Hispanic owners is 8.1 percentage points.

Because not all matches between the buyout and housing sales data are perfect, we restrict our sample to high quality matches to check the sensitivity of our results to mismatches. In

Figure 2: Price Discrepancy by Race



panel B of Table 3, we limit our sample to where there is an exact address match (i.e., based on street #, name, and type, pre/post direction, city, and ZIP code). We also restrict our sample to those where the owner last names match (when present in both the housing sales data and buyout data). Estimates are very similar to our baseline results in panel A using either or both sets of match quality sample restrictions.

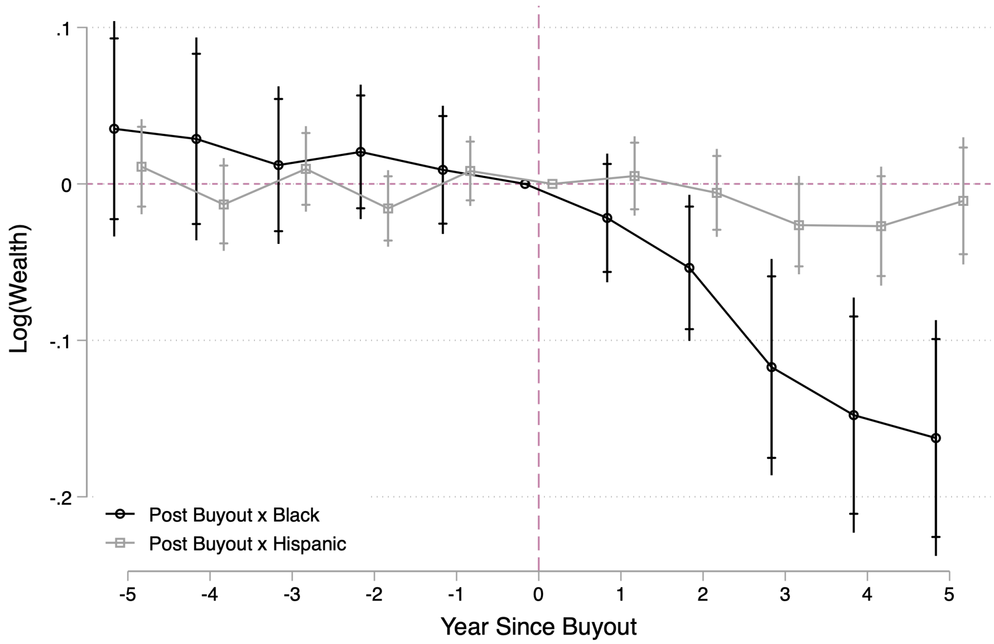
5.2 Wealth Accumulation and Income

We present impacts on wealth and income. Table 4 presents estimates from equation 3 with either the log of wealth or income as the dependent variable. All regressions include year, state of residence, and individual fixed effects. We find that after moving from the buyout property, wealth falls by close to 1.8 percent (column 1) and income falls by 2.2 percent (column 3).[16] When we interact the post-movement indicator with the discount in the buyout compensation (measured in $10,000's), we find that families with higher buyout discounts see a larger decrease in wealth and income after moving (columns 2 and 4). A $10,000 buyout discount reduces wealth by approximately 0.13 percent after the buyout. A similar negative impact of the buyout discount exists for income.

We test whether the impacts on wealth and income vary by race. Columns (1) and (3)

[16] Robust standard errors are calculated, but are currently not adjusted to account for the multi-stage estimation procedure and will be bootstrapped in the future.

Figure 3: Event Study of Wealth Impact



in Panel A of Table 5 present estimates from equation 5 respectively for $Race_i = Black_i$ and $Race_i = Hispanic_i$. Relative to white families, Black families see larger decreases in wealth after the buyout, whereas wealth impact for Hispanic families cannot be precisely measured. We plot the wealth impact for both groups over time in Figure 3.[17] The event study confirms that the impact on Hispanic families is small, unlike the impact on Black families, which also seems to be grow over time. When we additionally examine whether these effects vary with the level of the buyout discount, we find that the negative wealth effect of the discount is systematically larger for both Black and Hispanic families. This suggests that, compared to white families, minority families sustain larger damages to wealth from discounts in buyout compensation. Why this is the case may relate to racial disparities in social capital, including differences in trust and familiarity (Gaddis, 2012; MacDonald and Stokes, 2006) and access to information, expertise (Cornwell and Cornwell, 2008) and non-kinship networks (Gamoran et al., 2012) that facilitate connections to people of influence and status (Smith, 2000; McDonald and Day, 2010).

Table 5, panel B presents a similar set of regressions with income as the dependent variable.

[17] Specifically, we estimate

$$log(W_{i,t}) = \beta_0 + \sum_{\ell=-5}^{5} \beta_{1,\ell} Post_{i,T+\ell} + \beta_2 Race_i + \sum_{\ell=-5}^{5} \beta_{3,\ell} Post_{i,T+\ell} \times Race_i + \gamma_t + \eta_i + \epsilon_{i,t}$$

where $Post_{i,T+\ell}$ is now a set of indicators for the number of years since time T when the disaster event occurred for individual i. We plot $\beta_{3,\ell}$ for $\ell = [-5, 5]$ in Figure 3.

While we do not find evidence that the buyout process generally has a disproportionate impact on the income of minority owners (columns 1 and 3), the impact of discounts on income is still disproportionately larger for Black and Hispanic families (columns 2 and 4).

5.3 Neighborhood Change

If relocation and buyout compensation reduce wealth and, to some extent, income, then one would expect that they also detract from an individual family's ability to improve their situation and relocate to a higher quality neighborhood. In Table 6, we examine if the buyout discount changes the quality of the destination as measured by neighborhood characteristics, shown in the column header. On average, the buyout discount does not have a large impact on neighborhood quality. Of the precisely estimated impacts, the change in neighborhood quality represents an improvement of 1 percent or less relative to the mean. It is notable that families with no discounts seem to perform better overall after the buyout program, indicated by the coefficient on *Post*. This is somewhat unsurprising given survey evidence that many residents believed the buyout program would provide an opportunity to leave a declining neighborhood (Fraser et al., 2003).

While discounts have no overall impact on destination neighborhood quality, we consider whether their effect is disproportionately larger for minorities. These results are presented in Table 7 for Black (panel A) and Hispanic (panel B) owners. The coefficient of interest is $Post \times Race \times Discount$. For Black owners (panel A), we find that a lower buyout price has a larger negative impact on neighborhood quality than for white owners. Relative to the mean neighborhood characteristics in the period before the disaster, a $10,000 increase in buyout discount is associated with an increase in the share in poverty of 4.4 percent, an increase in the share of single parent households of 3.2 percent, and a decrease in the share employed in a skilled occupation of 1.5 percent. For Hispanic households, we similarly find that the same dollar value of buyout discount has a disproportionately large negative impact on neighborhood quality in terms of education, linguistic isolation, home ownership, and pollution. The coefficient on $Post \times Discount$ shows that no such impacts are found for white owners.

These findings support that lower compensation from buyout programs are more damaging to people of color in the long term. The challenge with inferring causality, however, is that those who are unable to secure fair compensation from buyouts (for example, due to bargaining ability, information, or discrimination) may also end up moving to poorer quality neighborhoods for the same reasons. Family fixed effects controls for many pre-determined factors (e.g., education of the household head). However, time-varying factors associated with the disastrous event that disproportionately affect people of color may still contribute to the disproportionate impacts of discounts that we find. While attributing neighborhood effects specifically to buyout compensation is difficult, it might be more reasonable to interpret these effects as being part of the general disproportionate impact of disasters, with potential exacerbation from policy interactions.

6 Robustness

We next assess the robustness of our findings. The first two sub-sections speak to threats to identification that could arise from features of the data, and the latter two sub-sections deal with other factors related to race that might explain our predicted price discount.

Selection into Buyouts If owners who are bad bargainers are more likely to participate in buyouts and race is correlated with bargaining ability due to education, access to expertise and information resources, then the differential buyout price compensation that we estimate reflects this rather than inequities that arise from the buyout program. To investigate this, we need information on owners that were offered but did accept the buyout. While administrative data on this group is not available, we proxy for this group of 'stayers' by finding all families living within 500 feet of any buyout property around the year of the disaster. We recovered 99,662 families near buyout properties, 52,454 of which were owners of primary residences.[18]

After having identified a set of stayer families, we estimate a logit model of the buyout participation decision as a function of wealth, owner race indicators, and interactions between race and wealth. We also include predicted market value (using the same procedure as predicting the market value for buyout properties) and length of residence. Table 8 presents the results from two different models that include wealth and predicted market value in levels or logs.

There are three significant predictors of participation: owner wealth, predicted property market value, and length of residence. Damages to valuable properties are unlikely to be fully covered by flood insurance given NFIP payout limits.[19] Owners of higher valued properties would thus be more likely to participate to recoup damage from limited coverage. It also intuitive that length of residence detracts from participation if neighborhood attachment and peer networks increase with tenure in a neighborhood. Finally, wealthier individuals are more likely to participate in buyouts. That our estimated price discrepancies are based on a wealthier sample of owners should not impact the racial price differential. The price discrepancies would only

[18] Of these families, 39,866 families do not move after the buyout (at least within our sample period), and 12,629 families eventually move at some point after the buyout.

[19] For example, the maximum building coverage for residential homes is $250,000.

be over-stated if the selection causes us to compare effective white bargainers with ineffective minority bargainers. The coefficients on the interactions between race and wealth in Table 8 do not lend support to this.

Differential Flood Insurance The FEMA buyout program removes undocumented flood insurance payouts to avoid duplication of benefits from its agency. Because we do not observe individual flood insurance participation or payouts, it is possible that the price differential that we measure is due to unobserved flood insurance compensation. This would be the case if payouts are undocumented because the owner kept the monetary assistance and minority owners are more likely to be insured.

We empirically examine whether this is the case by estimating the relationship between National Flood Insurance Program (NFIP) policies and tract level demographic characteristics. Specifically, we aggregate NFIP claims data to obtain the number of policy counts in a tract per year and the log of the average dollar amount of claims per policy. We then regress these measures of insurance takeup and claims on annual tract-level characteristics from the ACS.[20] Table 9 presents these estimates. All specifications include year and county fixed effects. These correlations suggest that Black and Hispanic households are less likely to have flood insurance (based on policy count) and have lower claims values (likely reflecting that these populations live in lower value housing), which is the opposite of what one would expect if our racial price discrepancies are being driven by Black and Hispanic households receiving compensation from insurance payouts.

Race-related Housing Market Frictions In panel A of Table 10, we explore the source of the price discrepancies we measure by augmenting the set of controls in the prediction discount model. In a friction-less market, demand characteristics, such as buyer and seller attributes, should not impact the hedonic equilibrium since the hedonic equilibrium is an envelope function that maps amenities to prices (Yinger and Nguyen-Hoang, 2016). However, recent work has provided ample evidence of housing market frictions that lead to different treatment of certain racial groups (Bayer et al., 2017; Christensen and Timmins, 2022; Aaronson et al., 2021). It is thus possible that the racial price discrepancies that we estimate are a result of systemic inequities arising from the housing market that lead us to over-predict the price that minority owners would receive in the market. To test this, we modify our hedonic prediction model (panel A, column 1) to include the race of the buyer (panel A, column 2), the race of the buyer and

[20] We take the midpoint of the 5-year ACS period as the year of the survey.

the seller (column 3), or the percent of Black and Hispanic buyers in a 5-year period at the Census block level of the property (column 4). Inclusion of buyer/seller race does not reduce the racial price discrepancy; if anything, the price discrepancy increases. We note, however, that some of the change in the point estimates is due to a change in the estimation sample. Since race predictions require buyer/seller names which are missing in some transactions, there are fewer observations in these regressions. When we re-estimate the price discount model using the smaller samples with the original hedonic prediction model (i.e., without buyer/seller race), estimates are not statistically different (Table A.1). This evidence points to the buyout process as a source of inequities.

Correlates of Race One might also question whether the racial price discounts that we find are due to correlates of race, specifically wealth, income, and skill. We next additionally control for these factors at the neighborhood (block group level) as of the year before the disaster event in the price discount model to test whether correlates of race are instead the drivers of our estimated price discounts (Table 10, panel B). When adding these controls, we find that the price differential for the Hispanic group disappears, but the discount for Black owners remains. While there is no longer a price discrepancy for Hispanic owners, we note that we also do not detect a price discrepancy for this group using the reduced sample without wealth controls (Table A.1). It is thus unclear the extent to which the price discount for Hispanics are driven by income. What is clear, however, is that the price discrepancy for Black owners is not solely an income story. It is notable that the percent of the block group that does not speak English has a large and statistically significant effect on the buyout discount, which points bargaining as being an important mechanism mediating inequitable buyout compensation.

7 Conclusion

In this paper, we investigate the equity impacts of the managed retreat, or "buyout", of flood-prone properties in the US. As flood risks continue to grow, buyouts are expected be increasingly used as an adaptation strategy. Our work is situated in the intersection of recent research highlighting the inequitable burdens of pollution and climate change (Banzhaf et al., 2019) and the impact of "place" in determining well-being and gaps in well-being (Chyn and Katz, 2021; Deryugina and Molitor, 2021). We document that buyout compensations are systematically lower for Black and Hispanic property owners relative to white owners when compared to the pre-disaster fair market value of their homes. We also find that buyout discounts lead participants to relocate in neighborhoods with higher social vulnerability, and that the discount is more damaging for people of color in terms of wealth accumulation and neighborhood change. In our context, a widely-used government adaptation policy, driven by aims of efficiency, may be a source of inequity and interact with neighborhood effects to perpetuate gaps in well-being across race.

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8 Tables

Table 1: Buyout Sample Census Block Characteristics (Year 2010)

	Full Sample		Matched CL		Matched Race		Matched InfoUSA		InfoUSA & Price Pred.	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	Mean	S.D.	Mean	t-stat	Mean	t-stat	Mean	t-stat	Mean	t-stat
White	0.77	0.28	0.71	-24.42	0.71	-13.53	0.76	-0.43	0.79	5.33
Black	0.10	0.21	0.15	17.08	0.12	0.39	0.10	-5.74	0.10	-3.98
Hispanic	0.06	0.14	0.07	13.23	0.08	15.24	0.07	4.79	0.04	-5.42
College	0.48	0.17	0.50	17.91	0.51	16.90	0.52	21.59	0.53	13.84
Poverty	0.13	0.13	0.14	-1.29	0.11	-13.21	0.10	-22.30	0.09	-15.51
Single Parent	0.35	0.24	0.37	8.17	0.35	-4.66	0.31	-16.03	0.31	-9.77
Skill	0.29	0.14	0.29	11.41	0.31	15.48	0.32	23.21	0.33	15.50
No English	0.03	0.07	0.04	13.48	0.05	17.32	0.03	3.67	0.02	-4.99
Owner	0.70	0.21	0.68	-5.91	0.69	1.41	0.72	11.88	0.73	8.29
Less than HS	0.17	0.12	0.17	-4.90	0.16	-10.06	0.13	-24.78	0.12	-21.34
PM25	10.05	1.89	10.11	6.22	10.13	4.49	9.95	-2.94	9.93	-2.37
Obs. (approx)	32,465		12,626		5,559		5,148		2,145	

Notes Table shows census block group characteristics as of the year 2010 for all buyouts (1-2), the sample that could be matched to Corelogic (3-4), the sample of buyouts for which we can identify buyer race (5-6), the buyouts in the matched Corelogic sample where we can track individuals in InfoUSA (7-8), the buyouts in the InfoUSA sample that have a price prediction (9-10). Observations are approximate because some fields are missing block group characteristics from the Census.

Table 2: Buyout Discount ($1,000's) by Race

Race	N	Mean	SD
White	5,902	49.11	83.56
Black	533	63.71	69.44
Hispanic	379	78.74	84.38
Total	6,814	51.90	82.93

Table 3: Percent Price Difference by Race

Panel A. Baseline Results

Prediction Model FE:	Tract & Yr	Blockgrp & Yr	Tract-by-Yr	Blockgrp-by-Yr
Black	-0.101***	-0.0998***	-0.106***	-0.0966***
	(0.0217)	(0.0215)	(0.0218)	(0.0214)
Hispanic	-0.0851***	-0.0837***	-0.0856***	-0.0814***
	(0.0212)	(0.0212)	(0.0210)	(0.0208)
Other	0.00866	0.00944	0.0151	0.0291
	(0.0959)	(0.0954)	(0.0912)	(0.0856)
Observations	5,775	5,775	5,775	5,774
R-squared	0.155	0.159	0.133	0.157

Panel B. Assess Match Quality

Subsample:	Baseline	Match Qual<3	Seller Last Name	Match Qual & Seller Name
Black	-0.0966***	-0.107***	-0.0766***	-0.0813***
	(0.0214)	(0.0206)	(0.0268)	(0.0262)
Hispanic	-0.0814***	-0.0846***	-0.0529**	-0.0644***
	(0.0208)	(0.0208)	(0.0241)	(0.0242)
Other	0.0291	0.0833	0.0999	0.0978
	(0.0856)	(0.0849)	(0.0810)	(0.0921)
Observations	5,774	5,324	3,827	3,611

Notes Table regresses the price difference between actual and predicted market price as a percentage of the market price on race indicators. In panel A, column headers indicate the set of spatial/temporal fixed effects included in the hedonic prediction model (to estimate $\hat{P}_{k,t}$ from equation 1). In panel B, we restrict our sample to higher quality matches between the buyout and housing sales data. Restrictions include observations where a) there is an exact address match, b) the owner last name match, and c) both owner last name and address match. All price discount regression models include year of sale and state fixed effects.

Table 4: Buyout Impact on Wealth and Income

Dep. Var.:	Wealth		Income	
	(1)	(2)	(3)	(4)
Post Buyout	-0.0176***	-0.00846*	-0.0218***	-0.0178
	(0.00272)	(0.00441)	(0.00771)	(0.0124)
Post x Discount		-0.00134***		0.00300***
		(0.000321)		(0.000920)
Observations	48,745	23,127	48,745	23,127
R-squared	0.828	0.817	0.673	0.663

Notes The dependent variables in the table is the log of wealth or income (in \$1,000's). Post = 1 if the time period is after a buyout move, and 0 if the time period is before the fiscal year of the buyout. Discount = (Predicted - Actual)/\$10,000. All regressions include year, state of residence, and individual fixed effects. Robust standard errors in parentheses.

Table 5: Buyout Impact on Wealth

	Panel A: Log(Wealth)			
	Race = Black		Race = Hispanic	
	(1)	(2)	(3)	(4)
Post	-0.00941**	-0.00658	-0.0117***	-0.00912**
	(0.00439)	(0.00452)	(0.00437)	(0.00450)
Post x Race	-0.128***	-0.0957***	0.00486	0.0139
	(0.0248)	(0.0252)	(0.0148)	(0.0155)
Post x Discount		-0.000996***		-0.000938***
		(0.000326)		(0.000327)
Post x Race x Discount		-0.00814***		-0.00263*
		(0.00273)		(0.00148)
Observations	22,096	22,096	22,640	22,640
R-squared	0.821	0.821	0.817	0.817

	Panel B: Log(Income)			
	Race = Black		Race = Hispanic	
	(1)	(2)	(3)	(4)
Post	-0.00790	-0.0184	-0.00455	-0.0153
	(0.0128)	(0.0129)	(0.0127)	(0.0128)
Post x Race	-0.0487	0.00336	-0.0514	-0.0317
	(0.0583)	(0.0587)	(0.0338)	(0.0347)
Post x Discount		0.00387***		0.00392***
		(0.000963)		(0.000962)
Post x Race x Discount		-0.0146**		-0.00676*
		(0.00636)		(0.00362)
Observations	22,096	22,096	22,640	22,640
R-squared	0.664	0.664	0.663	0.663

Notes Dependent variable in the table is log(wealth) in panel A and log(income) in panel B. Post = 1 if the time period is after a buyout move, and 0 if the time period is before the fiscal year of the buyout. Specification includes year, state of residence, and family FE. Robust standard errors in parentheses.

Table 6: Neighborhood Change and Buyout Discount

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. Var.:	Poverty	Single Parent	PM2.5	Skill	No English	Owner	Log(RSEI)
Post	-0.0161***	-0.0327***	-0.0107***	0.0444***	-0.00944***	0.0262***	-0.134**
	(0.00313)	(0.00744)	(0.00239)	(0.00398)	(0.00133)	(0.00570)	(0.0582)
Post x Discount	-0.000155	-0.000286	-0.000820***	-6.60e-05	-0.000229***	0.00224***	-0.00570
	(0.000176)	(0.000436)	(0.000138)	(0.000245)	(8.77e-05)	(0.000381)	(0.00395)
Observations	13,443	13,378	13,443	13,443	13,443	13,443	10,793
Dep. Var. Mean	0.0851	0.292	0.117	0.405	0.0225	0.741	6.722

Table 7: Neighborhood Change by Discount and Race

Panel A. Black

Dep. Var.:	Poverty	Single Parent	Less than HS	Skill	No English	Owner	Log(RSEI)
Post	-0.0163***	-0.0339***	-0.00954***	0.0431***	-0.00864***	0.0290***	-0.128**
	(0.00319)	(0.00766)	(0.00243)	(0.00403)	(0.00131)	(0.00578)	(0.0599)
Post x Discount	-0.000286	-0.000573	-0.000897***	3.21e-05	-0.000332***	0.00254***	-0.00828**
	(0.000186)	(0.000458)	(0.000148)	(0.000250)	(8.80e-05)	(0.000391)	(0.00417)
Post x Black	-0.0123	0.0500*	-0.00118	0.0168	0.00660	-0.0332	-0.331
	(0.0107)	(0.0273)	(0.00740)	(0.0170)	(0.00676)	(0.0277)	(0.235)
Post x Black x Discount	0.00376***	0.00926***	0.000367	-0.00624***	0.000722	-0.00301	0.0243
	(0.000840)	(0.00238)	(0.000551)	(0.00175)	(0.000656)	(0.00257)	(0.0226)
Observations	12,912	12,847	12,912	12,912	12,912	12,912	10,369
Dep. Var. Mean	0.0851	0.292	0.117	0.405	0.0225	0.741	6.722

Panel B. Hispanic

Dep. Var.:	Poverty	Single Parent	Less than HS	Skill	No English	Owner	Log(RSEI)
Post	-0.0163***	-0.0353***	-0.0108***	0.0416***	-0.0102***	0.0303***	-0.141**
	(0.00319)	(0.00758)	(0.00242)	(0.00402)	(0.00134)	(0.00573)	(0.0596)
Post x Discount	-0.000290	-0.000624	-0.000896***	-7.95e-07	-0.000325***	0.00258***	-0.00803*
	(0.000186)	(0.000457)	(0.000148)	(0.000250)	(8.79e-05)	(0.000391)	(0.00416)
Post x Hispanic	0.00654	0.00167	-0.0269***	0.0362***	-0.00313	-0.0234	0.0849
	(0.00765)	(0.0177)	(0.00709)	(0.0131)	(0.00659)	(0.0196)	(0.142)
Post x Hispanic x Discount	0.000193	0.000846	0.00146**	0.00211*	0.00144**	-0.00411**	0.0273**
	(0.000631)	(0.00176)	(0.000595)	(0.00112)	(0.000566)	(0.00207)	(0.0126)
Observations	13,161	13,096	13,161	13,161	13,161	13,161	10,563
Dep. Var. Mean	0.0851	0.292	0.117	0.405	0.0225	0.741	6.722

Notes Table estimates the disproportionate effect of buyout discounts on neighborhood quality. The dependent variables (noted in column headers) represent the Census block group characteristic a share. All specifications include year, state, and family fixed effects. Robust standard errors in parentheses.

Table 8: Selection into Buyout Participation

Dep. Var.: Participation Indicator	(1) Linear	(2) Log
f(wealth)	0.0415***	1.177***
	(0.00253)	(0.0777)
Black	-0.332	-0.353
	(0.283)	(2.116)
Hispanic	0.281	-1.504
	(0.298)	(2.412)
Other	-0.786	-8.717
	(0.801)	(7.406)
f(wealth) x Black	-0.0118	-0.0356
	(0.00943)	(0.268)
f(wealth) x Hispanic	0.0108	0.264
	(0.0108)	(0.307)
f(wealth) x Other	0.0241	1.090
	(0.0270)	(0.936)
Predicted Market Value	-4.23e-07*	-0.0952***
	(2.55e-07)	(0.0300)
Length of Residence	-0.00676***	-0.00715***
	(0.00160)	(0.00161)
Constant	-4.419***	-11.49***
	(0.0818)	(0.684)
Observations	104,686	103,777

Notes Table estimates logit models, where the dependent variable is a binary indicator for participation in the buyout program. Column 1 introduces wealth and market price in levels and column 2 introduces these variables in logs.

Table 9: NFIP Policies/Claims and Demographic Characteristics

Dep. Var.:	Policy Count	Log of Claim per Policy ($)
Median Income	1.80e-06	2.41e-06***
	(8.05e-06)	(8.64e-07)
% Black	-0.0887***	-0.0114***
	(0.00931)	(0.000999)
% Hispanic	-0.0987***	-0.0106***
	(0.0166)	(0.00178)
% Asian	-0.188***	-0.0222***
	(0.0300)	(0.00321)
% ≥Bachelors	-0.00839	-0.0153***
	(0.0143)	(0.00153)
% Limited English	0.0278	0.00282
	(0.0351)	(0.00377)
Constant	10.59***	7.029***
	(0.659)	(0.0707)
Observations	77,999	77,996
R-squared	0.078	0.120

Notes This table estimates the correlation between NFIP participation/claims and demographic charactersitics. The dependent variables are NFIP policies in a tract and year (column 1) and the average dollar value of claims per policy (column 2).

Table 10: Percent Price Difference by Race, Augmented

Panel A: Prediction Model Controls

	Baseline:	Buyer Race	Buyer & Seller Race	Block Buyer Race
Black	-0.0966***	-0.191***	-0.155**	-0.181***
	(0.0214)	(0.0675)	(0.0733)	(0.0669)
Hispanic	-0.0814***	-0.247***	-0.197**	-0.241***
	(0.0208)	(0.0716)	(0.0831)	(0.0723)
Other	0.0291	-0.0913	0.0888	-0.0796
	(0.0856)	(0.141)	(0.0832)	(0.141)
Observations	5,774	1,068	872	1,068
R-squared	0.157	0.161	0.180	0.163

Panel B: Price Discount Model Controls

	Baseline	Wealth & Income	% No English	% HS Degree
Black	-0.0966***	-0.0738*	-0.118**	-0.117**
	(0.0214)	(0.0431)	(0.0519)	(0.0518)
Hispanic	-0.0814***	0.0213	0.0362	0.0385
	(0.0208)	(0.0404)	(0.0423)	(0.0418)
Other	0.0291	0.0255	0.0790	0.0946
	(0.0856)	(0.125)	(0.122)	(0.121)
Log(wealth)		0.251***	0.204***	0.175**
		(0.0616)	(0.0676)	(0.0704)
Log(income)		0.120***	0.111***	0.107***
		(0.0173)	(0.0195)	(0.0199)
% No English			-0.00708***	-0.00752***
			(0.00245)	(0.00247)
% High School				-0.00230**
				(0.00115)
Observations	5,774	1,953	1,561	1,561
R-squared	0.157	0.184	0.220	0.222

Notes Table regresses the price difference between actual and predicted market price as a percentage of the market price on race indicators, but augments the prediction model (panel A) or the price discount model (panel B) in several ways. In panel A, headers indicate the additional controls included in the *prediction* model (equation 1): buyer race, buyer and seller race, or buyer minority share in the block . Panel B presents estimates that add control for correlates of race in the *price discount* model (equation 2): Log of wealth or income, % no English, and % with a high school degree only. All price discount regression models include year of sale and state fixed effects.

A Apppendix

Table A.1: Robustness - Percent Price Difference by Race

	Panel A. Augmented Model			
	Prediction: Buyer Race	Prediction: Buyer & Seller Race	Prediction: Block Buyer Race	Price Discount: Wealth Controls
Black	-0.191***	-0.155**	-0.181***	-0.117**
	(0.0675)	(0.0733)	(0.0669)	(0.0518)
Hispanic	-0.247***	-0.197**	-0.241***	0.0385
	(0.0716)	(0.0831)	(0.0723)	(0.0418)
Other	-0.0913	0.0888	-0.0796	0.0946
	(0.141)	(0.0832)	(0.141)	(0.121)
Observations	1,068	872	1,068	1,561
R-squared	0.161	0.180	0.163	0.222
	Panel B. Baseline Model with Augmented Model Sample			
	Sample: Buyer Race	Sample: Buyer & Seller Race	Sample: Block Buyer Race	Sample: Wealth Controls
Black	-0.160***	-0.170**	-0.160***	-0.127**
	(0.0618)	(0.0710)	(0.0618)	(0.0532)
Hispanic	-0.235***	-0.224***	-0.235***	0.0168
	(0.0673)	(0.0776)	(0.0673)	(0.0442)
Other	-0.102	0.0184	-0.102	0.132
	(0.120)	(0.0849)	(0.120)	(0.0965)
Observations	1,068	872	1,068	1,561
R-squared	0.155	0.174	0.155	0.173

Notes Table regresses the price difference between actual and predicted market price as a percentage of the market price on race indicators. Panel A reproduces the estimates in panel B of Table 10. Panel B in this table re-estimates the price discount model using the smaller samples in panel A but with the original hedonic prediction model (i.e., without buyer/seller race). All prediction models include block group-by-year fixed effects.