

Racial Gaps in Federal Flood Buyout Compensations

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Rising temperatures from climate change have led to increased risk of coastal and riverine flooding (Wing et al., 2022; Swain et al., 2020). As of 2020, the average annualized flood loss is estimated to be \$32.1 billion, where losses are expected to grow disproportionately in communities of color (Wing et al., 2022). Managed retreat from flood-prone areas, commonly known as ‘buyouts,’ is one strategy to adapt to growing flood risk. In a typical 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.

This study examines the role of race and ethnicity in an important buyout outcome – the compensation received by the homeowner. Using a nationwide sample of Federal Emergency Management Agency (FEMA) buyout acquisitions and the universe of US housing transactions over the last two decades, we estimate whether the discount in buyout price compensation, calculated as the buyout price that owners received less the fair-market value (FMV) that they would have received based on a hedonic prediction model, systematically varies by the homeowner’s race.

While this is not the first study to examine equity issues in managed retreat programs, ours is the first to provide systematic evidence of inequitable compensation using nationwide, administrative data. As housing is a large source of wealth for households in the US, disproportionate compensation, in an attempt to adapt to the effects of a warming climate, may further widen the wealth and social mobility gap.

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I. Equity in Managed Buyouts

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, 2014). When a PDD occurs, the state or local government must submit an application to request funding for buyouts. If the application is successful and owners agree to sell, then the property is demolished and the land is maintained as open space. From 1989 to 2017, FEMA funded 43,633 buyouts of flood-prone properties across 1,148 counties in 44 states (Mach et al., 2019).

While FEMA states that buyouts are strictly voluntary, 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 al., 2019; Elliott, Brown and Loughran, 2020; Tate et al., 2016). Specific features of the program also place disproportionate burden on low SES groups that cannot afford to remain in their community (De Vries and Fraser, 2012; Dineva et al., 2021).

II. Data

Our analysis draws from two main sources: FEMA buyout data and property sales transactions from Corelogic, Inc. The FEMA buyout data were obtained by National Public Radio through a Freedom of Information Act request. The data cover 41,004 buyouts between 1989 and 2017 and include the address of the buyout property, fiscal year of the buyout program, owner

name, price paid, owner occupancy type, and house structure. Proprietary property sales data from Corelogic, Inc. provide property attributes (e.g., address, age, number of bathrooms, square footage, etc.) as recorded from tax assessments for over 149 million parcels and property sales and refinance information (e.g., sale date, sale amount, and buyer and seller names) from over 575 million deed transactions.

We identify the transaction in the property sales data that corresponds to each buyout property to recover the actual buyout price, date of sale, and owner involved.¹ This is accomplished by first identifying the *parcels* in the Corelogic data that are associated with the buyout properties based on address information and then the first sales transaction for each buyout property during or after the fiscal year of the corresponding buyout project. There were 41,004 properties in the buyout data. After removing non-residential, non-primary, manufactured homes, we are left with 34,441 properties.² Of these buyout properties, we matched 17,204 (50%) in the Corelogic data based on street number, name, ZIP code, city, and county FIPS code information. We lose some additional buyouts when trying to identify the sales transaction. This leaves 13,475 buyout properties that are matched to housing transactions.³

Next, we identify the race of the owner using probabilistic matching (Imai and Khanna, 2016), which predicts individual-level race and ethnicity (i.e., white, Black, Hispanic, or some other race) based on the owner’s surname and county of residence. We recover race for 53% of the buyout properties matched to sales transactions. Finally, after removing transactions with missing prices and then trimming the top and bottom 1 percent of the price distribution to remove outliers (likely driven by recording errors or multi-unit dwellings),

¹Buyout prices and owner names from the NPR FOIA data are frequently missing.

²We remove mobile homes and those that are not primary residences since the property owner is different from the resident.

³In some cases, buyout properties are matched to the same property in Corelogic. These are dropped.

we are left with a final sample of 5,948 matched buyout properties with both information on buyout sales price and homeowner race. In the Online Appendix, we show that the sample of Corelogic matches is generally comparable to the full sample in terms of neighborhood characteristics, but is slightly more diverse (Table A.1).

III. Empirical Strategy

We estimate a hedonic model using the sample of *non-buyout* properties to recover a pre-disaster, fair-market value (FMV) for each buyout property. We pay particular concern to the fact that minorities tend to live in low amenity areas with lower value housing due to income or historical factors. Ignoring such 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 concern, we estimate the model separately by county and control for block group-by-year fixed effects ($\eta_{b,t}$) in addition to controlling for housing characteristics (X_{jt}). For a house j sold at time t , we estimate the following hedonic model, which we refer to as the ‘prediction model’, using all non-buyout houses j in county c :

$$(1) \quad P_{j,t} = \alpha_{0,c} + \alpha_{1,c}X_{jt} + \eta_{b,t} + \epsilon_{j,t}$$

The (county-specific) parameters estimated from the hedonic prediction model are used to predict the FMV of buyout properties located in the corresponding county; X_{jt} includes living square footage, total baths, land square footage, number of bedrooms, age, and indicators for single family, condo, apartment, new construction, and mobile home; $\epsilon_{j,t}$ represents an idiosyncratic unobserved error. 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 one-percent of the price distribution in each state.

Next, we calculate the percent discount using the actual and predicted FMV of each buyout property and regress the buyout discount on homeowner race indicators. Let $P_{k,t}$ represent the actual buyout price of house k ; $\hat{P}_{k,t}$ represents the hedonic prediction; $Black_i$, $Hispanic_i$, and $Other_i$ denote indicators for homeowner i 's race (the omitted group for comparison is white owners). Using all buyout houses k sold at time t (occupied by household i), we estimate a 'price discount model' as:

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

We additionally control for unobserved differences across state-level buyout programs using state fixed effects (θ_s) and fluctuations over time with year fixed effects (γ_t).

IV. Results

A. Main Results

Figure 1 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: white, Black, and Hispanic owners respectively receive an average discount of approximately \$49,000, \$63,000, and \$78,000. Panel A of Table 1 presents the baseline price discrepancies as a percentage as estimated from equation 2. We present estimates that use various spatial fixed effects in the hedonic prediction (indicated in the column headers) to construct the buyout discount. Robust standard errors are included.

Black and Hispanic owners receive a buyout discount compared to white owners, regardless of the specification used in the he-

donic prediction. In our preferred model (column 4), which adjusts for block group-specific time trends in the hedonic prediction, we find that Black owners receive a price discount that is 10.3 percentage points lower than white owners. The relative discount for Hispanic owners is 8.3 percentage points.

B. Robustness

We assess the robustness of our findings in Panel B of Table 1, where all specifications include (at a minimum) block group-specific time trends in the hedonic prediction. First, because matching between the buyout and housing sales data is imperfect and there may be recording errors in the buyout data, we restrict our sample to transactions where one can be more confident that the sale is a buyout transaction. Column 1 restricts the sample to buyouts where the recorded buyer is a state or local government (e.g., municipality or special district), and column 2 restricts the sample to those where the seller's last name as recorded in the buyout data matches the last name recorded in the housing data (when available). Estimates are very similar to our baseline results in panel A.

A second data-related concern is that FEMA deducts National Flood Insurance Program (NFIP) flood insurance payouts from the buyout payment, but 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 if minority owners are more likely to be insured. However, in supplemental analysis, we find that Black and Hispanic households are less likely to have flood insurance (based on NFIP policy counts) and have lower claim values per policy (Online Appendix, Table A.2). This 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.

Third, we explore whether the source of price discrepancies stem from housing market frictions that cause minority buy-

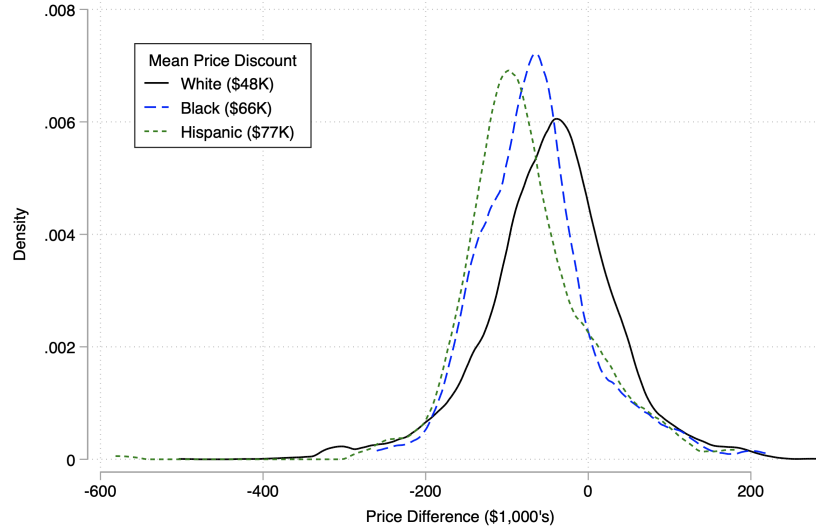


Figure 1. : Price Discrepancy (in \$1,000's) by Race

ers to be treated differently (e.g., Bayer et al. (2017) and Christensen and Timmins (2022)) rather than the buyout program. If so, including the race of the homebuyer in the hedonic *prediction model* (equation 1) should diminish the price discount that we measure in equation 2. However, inclusion of buyer race does not reduce the racial price discrepancy (panel B, column 3); if anything, the price discrepancy increases.⁴ This evidence points to the buyout process as a source of inequities rather than housing market discrimination.

One might also question whether correlates of race are instead the drivers of our estimated price discounts. We additionally control for poverty and linguistic isolation at the neighborhood (block group level) as of the year before the disaster event in the price discount model. We find that the price differential for the Hispanic group disappears, but the discount for Black owners remains (panel B, column 4). While there is no longer a price discrepancy for Hispanic owners, we note that we also do not detect a statistically significant price discrepancy for this group using the reduced sample with-

⁴We note, however, that some of the change in the point estimates is due to a change in the estimation sample due to missing buyer names.

out controls for race correlates (Online Appendix, Table A.3). It is notable, however, that the price discount with neighborhood controls is a third of the estimate without these controls, conditional on the sample. This suggests that bargaining ability may be an important mechanism driving disparities in compensation for Hispanic owners. These results also suggest that the price discrepancy for Black owners is not solely due to income.

V. Discussion

We document that buyout compensations from a widespread Federal program are systematically lower for Black and Hispanic property owners relative to white owners. In light of the impact of ‘place’ in determining well-being (Chyn and Katz, 2021; Deryugina and Molitor, 2021), such inequitable compensation is likely to exacerbate the racial gap in social mobility by disproportionately limiting the relocation options for people of color. The equity impacts of this climate adaptation strategy are equally important for understanding its long-term welfare implications, particularly since managed retreat may be an unavoidable option going forward as climate-induced flood risks continue to grow (US-

GCRP, 2018; Carey, 2020).

Table 1: Differential Price Compensation by Race

Panel A				
Prediction Model FE:	Tract & Year (1)	Blockgrp & Year (2)	Tract Trends (3)	Blockgrp Trends (4)
Black	-0.106 (0.0215)	-0.105 (0.0213)	-0.110 (0.0215)	-0.103 (0.0213)
Hispanic	-0.0867 (0.0213)	-0.0853 (0.0212)	-0.0870 (0.0210)	-0.0833 (0.0208)
Other	0.00934 (0.0965)	0.0101 (0.0960)	0.0154 (0.0920)	0.0296 (0.0861)
Observations	5,619	5,619	5,619	5,618
R-squared	0.156	0.160	0.133	0.159
Panel B				
Robustness Checks:	Govt Buyer (1)	Seller Match (2)	Race in Prediction (3)	Race Correlates (4)
Black	-0.0949 (0.0231)	-0.0741 (0.0263)	-0.191 (0.0675)	-0.0998 (0.0409)
Hispanic	-0.0596 (0.0224)	-0.0526 (0.0241)	-0.247 (0.0716)	-0.000511 (0.0359)
Other	0.0544 (0.101)	0.100 (0.0810)	-0.0913 (0.141)	0.210 (0.0890)
% English				-0.00417 (0.00218)
% Poverty				-0.396 (0.100)
Observations	4,147	3,827	1,068	2,179
R-squared	0.213	0.173	0.161	0.194

Note: Table regresses the price difference between actual and predicted market price as a percentage of the market price on race indicators. Panel A presents estimates using different spatial/temporal fixed effects in the hedonic prediction model (denoted in the header). Panel B tests the robustness of the estimates to different samples and hedonic prediction controls. All price discount regression models include year of sale and state fixed effects. Robust standard errors in parentheses.

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