Three Essays on Residential Sorting and Flood Buyout Programs

By Emma Donnelly

August 2025

Prospectus Examination

Advisory Committee:

Dr. Michael Delgado (co-chair)

Dr. Carson Reeling (co-chair)

Dr. Maria Marshall

Dr. Lala Ma (external)

Dr. Max Melstrom (co-chair)

Abstract

This prospectus outlines three essays that analyze the factors influencing residential sorting in the context of a flood buyout program. Chapter 1 examines the effect of participating in a voluntary buyout program and the consequences of rejecting a buyout offer, using a two-stage residential sorting model. Chapter 2 explores the willingness to pay for flood risk avoidance through a voluntary buyout program and evaluates the welfare effects of accepting a buyout offer. It also compares these effects across different racial and income groups, using a two-stage sorting model alongside a general equilibrium counterfactual analysis. Chapter 3 extends this analysis to a mandatory buyout program, using the same two-stage sorting model and general equilibrium counterfactual framework to assess its economic effects and distributional consequences across racial and income groups.

1. **Introduction**

Flooding is one of the most damaging and costly consequences of climate change, increasingly threatening infrastructure, homes, and entire communities. As flood events grow in intensity and frequency, governments have adopted flood buyout programs as a strategy to reduce long-term risk. These programs involve agencies purchasing homes in flood-prone areas from voluntary participants and converting them into open or green spaces to prevent future damage. Over 229,000 U.S. homes have sustained repeated flood damage in the past two decades, and more than 1,100 local governments across 49 states have implemented such programs (Siders, 2021).

Despite their intent to reduce flood risk, federal buyout programs often reinforce existing social and racial inequities. Evidence is mixed regarding environmental justice concerns with who is offered buyouts. Some studies find that buyouts are more likely to be implemented in whiter (Elliott et al., 2020; Hashida & Dundas, 2023) and higher-income counties with larger populations (Mach et al., 2019). Others show that neighborhoods historically shaped by housing discrimination are disproportionately targeted for buyouts (Zavar & Fischer, 2021), and that targeted properties tend to be concentrated in areas with lower social privilege (Mach et al., 2019). Concerns have been raised about inadequate relocation support for low-income and minority communities (Siders, 2019; Shi et al., 2022; Marino, 2021). There is evidence that financial buyout offers are disproportionately lower for Black and Hispanic residents compared to White residents (Jowers et al., 2023). In Harris County, Texas, the buyout program has faced criticism for disproportionately affecting low- and moderate-income Latino residents, many with mixed or undocumented status (Bonnyman, 2024). Understanding the distributional impacts of buyouts is thus critical for both climate adaptation and social justice.

Prior research has evaluated flood buyouts using hedonic pricing and contingent valuation methods (CVM) (Guo, 2023; Nelson, 2020; Ando, 2022; Jowers, 2023; Bonnyman, 2024; Holloway, 2023; Hashida, 2023). However, estimating willingness to pay (WTP) for flood risk is complicated by its correlation with desirable amenities like coastal access (Bakkensen & Ma, 2020), and these existing methods face important limitations in disentangling these effects.

Compared to CVM, which relies on hypothetical scenarios, residential sorting models are grounded in actual behavior, avoiding biases like hypothetical, strategic, and anchoring effects (Murphy & Stevens, 2016). They more credibly estimate how households trade off housing costs and environmental risks.

Compared to hedonic models, which regress home prices on observed characteristics, sorting models address omitted variable bias and price endogeneity. Hedonic methods are better for marginal changes, whereas sorting models can evaluate large-scale policy impacts, such as buyouts that reshape residential patterns. They also account for endogenous amenities and sorting dynamics that can bias hedonic estimates. Sorting models allow for disaggregated welfare analysis by household characteristics, offering clearer insights into distributional and equity impacts than CVM or hedonic approaches (Klaiber & Kuminoff, 2014).

While relocating people from their homes and communities is controversial such programs represent a potentially effective way to protect homeowners from escalating flood risks. Given projections of sea level rise and the increasing use of buyouts across the U.S., it is crucial to examine their welfare impacts. In my prospectus, I propose a residential sorting model to examine the economic effects of voluntary and mandatory flood buyout programs on people living in or near buyouts. I will use a sorting model to estimate households’ willingness to estimate households’ willingness to accept flood risk by rejecting a buyout offer and remaining in a flood-zone. I will also use the sorting model to estimate households’ willingness to pay (WTP) to avoid flood risk through participation in voluntary and mandatory flood buyout programs. I will also examine the distributional consequences of buyout programs by including heterogeneous preferences by race and income group in order to get estimates of utility of different race and income groups.

This research investigates three central questions related to household preferences and decision-making in the context of flood risk and buyout programs. First, *what are households willing to accept (WTA) to remain in flood-prone areas and reject a flood buyout offer? How do these valuations vary by race and income?* I hypothesize that WTA to remain in flood-prone areas is negative, especially where buyouts have been implemented nearby. Second, *what are people willing to pay (WTP) to avoid flood risk through voluntary participation in flood buyout programs, and how do these valuations differ across racial and income groups?* I hypothesize that WTP to avoid flood risk through voluntary buyouts is positive. Third, *what are people willing to pay to avoid flood risk through mandatory flood buyout programs, and how do these valuations vary by race and income?* I hypothesize that WTP for participation in mandatory programs may differ from voluntary programs.

These questions are grounded in a utility-based framework of residential choice, where individuals evaluate whether to or accept a buyout based on the costs and benefits associated with each option. The mechanisms that may influence a decision are discussed in section 3, and range from structural housing attributes and neighborhood amenities to program trust, social networks, and psychological relocation costs. These mechanisms enter into this decision-making process. They shape the utility people derive from living in their current location versus relocating through a buyout.

For the first research question, I hypothesize WTA will be negative, as rejecting a buyout likely reduces home values due to ongoing flood exposure and the “checkerboard effect.” This term refers to the patchy pattern that emerges when only some households accept buyouts while others remain, leading to neighborhoods with interspersed vacant lots. The resulting fragmentation can contribute to property value decline, reduce municipal service efficiency, and undermine community cohesion (Horn, 2024). I hypothesize that remaining in such areas lowers household utility, such that compensation would be required to justify staying. However, I expect this WTA to vary by race and income. Minority and lower-income households may experience greater barriers to relocation, including higher moving costs, stricter credit constraints, or limited familiarity with bureaucratic processes. Stronger social ties, cultural familiarity, and language communities may also anchor them in place. These factors may reduce the disutility of remaining, resulting in a less negative WTA. This should not be interpreted as a preference for flood risk, but rather as an outcome of constrained housing markets and structural inequalities.

For the second research question, I hypothesize that WTP to participate in a voluntary buyout program is positive. Households benefit from exiting high-risk areas and gaining financial, physical, and psychological security, and these benefits are likely capitalized into home values. Risk aversion, expectations about future flood events, and trust in public institutions also contribute to utility gains from participation. However, I anticipate heterogeneity in observed WTP. While higher-income households may be more likely to act on flood risk perceptions due to fewer constraints, lower-income and minority households may struggle to convert risk aversion into action because of barriers to buyout participation. As a result, their observed WTP may appear lower, even if their underlying preference for risk reduction is similar.

For the third research question, I hypothesize that WTP to participate in a mandatory buyout program remains positive, but is lower on average compared to voluntary programs. Although mandatory programs offer safety and housing quality improvements, the absence of choice and potential perceptions of coercion may reduce overall utility. In these settings, perceived fairness, procedural transparency, and institutional trust become even more critical. As with the voluntary context, I expect significant variation in WTP by race and income. Lower-income and minority households may have lower observed WTP due to structural housing disadvantages, relocation challenges, or heightened vulnerability to displacement harms. These households may also experience institutional mistrust, language or cultural barriers, or fears related to immigration status. However, in jurisdictions where programs provide culturally competent outreach, inclusive eligibility criteria, and relocation support, these disutilities may be mitigated. In such cases, some households may view mandatory buyouts as opportunities for improved housing access or upward mobility, leading to higher WTP relative to less supportive program environments.

Overall, I expect WTP in mandatory programs to reflect both the tangible benefits of reduced flood exposure and the intangible costs of forced relocation. For historically marginalized groups, WTP may be shaped more by the perceived fairness and accessibility of the program than by flood risk itself. Thus, WTP should not be interpreted narrowly as a measure of risk aversion but more broadly as a reflection of preferences, constraints, and the quality of policy design. In summary, heterogeneity in WTP and WTA across racial and income lines underscores the importance of interpreting these valuations in context, considering both structural barriers and enabling conditions.

Harris County, Texas, is a critical case. It has implemented the most buyouts of any U.S. county and has operated one of the nation’s longest-standing voluntary programs. This study uses detailed records on over 3,800 buyouts across 19 watersheds from the Harris County Flood Control District, combined with housing transactions, floodplain maps, and neighborhood data. A supplemental dataset on relocation addresses supports robustness checks. Quantifying the economic effects of buyouts is essential, especially given their cost. According to the National Institute of Building Sciences, every $1 spent on buyouts generates $5 to $9 in benefits (Siders, 2021).

**2. Background**

**2.1 Policy Context**

Climate-related disasters in the United States, particularly flooding, are becoming increasingly frequent and costly. In response, policymakers have turned their attention to flood buyouts, which are the purchase of flood-prone properties to relocate residents and prevent future damage. These properties are then left as open greenspace, halting future damage costs at the point of purchase while providing ecosystem services. While buyouts offer long-term cost savings and resilience benefits, they also raise critical questions about equity, implementation, and the lived experiences of those affected.

Flooding is a significant concern to the 4.7 million residents of Harris County, Texas. As a fast-growing, flood-prone urban area with deep socioeconomic and racial divides, it has become a national focal point for flood buyout programs. The county’s geography and development patterns, characterized by vast impervious surfaces and an extensive bayou system, make it particularly vulnerable to heavy rainfall and storm surges. These problems are exacerbated by poor urban planning and consistent population growth. Despite the frequency and severity of flooding events, development is still permitted in the one percent floodplain. Hurricane Harvey in 2017 was a turning point, causing catastrophic flooding and prompting a surge in federal disaster funds. In the aftermath, Harris County voters approved a $2.5 billion bond for flood mitigation, with a portion allocated to property buyouts.

The Harris County Flood Control District (HCFCD), created in 1937, oversees local buyout efforts. The district uses both Federal Emergency Management Agency (FEMA) and Housing and Urban Development (HUD) funding, along with additional local contributions. HCFCD’s buyout program is voluntary and prioritizes properties with repetitive loss claims or homes in deep floodplains. It also considers social vulnerability factors such as income, age, and language when selecting neighborhoods. The buyout process typically begins with outreach to high-risk areas, followed by appraisals, negotiations, and relocation support. Once properties are purchased, homes are demolished, and the land is converted into permanent greenspace (Bonnyman, 2024). The voluntary buyout program has been in place since 1985, with buyouts significantly increasing since Hurricane Harvey in 2017. As of 2023, over 3,500 properties have been purchased, making this the program with the highest number of buyouts in the United States (Binder, Greer, & Zavar, 2023). In addition to the voluntary program, a mandatory buyout program known as Project Recovery was initiated in 2020, with buyouts beginning in 2021 (Bonnyman, 2024). Figures 1 and 2 map the geographic boundaries of the flood buyout program and the demographic distribution of the county, respectively.

**2.2 Economic research on flood buyout programs**

Prior research suggests that flood buyout programs generate economic benefits. One potential channel is through reducing exposure to flood risk. When residents relocate to safer areas that remain near their original communities, they can continue contributing to local economies while avoiding future damage (Elliott et al., 2023). Buyouts may also steer future development away from high-risk zones, helping to contain long-term public costs (Hashida & Dundas, 2023). These outcomes are particularly relevant given that, since 1998, only about 4.5% of FEMA’s disaster funding has gone toward buyouts, and participation remains limited due to residents’ concerns over fair compensation, displacement, and attachment to place. Local governments may also be hesitant to promote buyouts, fearing they signal long-term risk and depressed property values (Hashida & Dundas, 2023). The voluntary nature of most buyout programs plays a key role in shaping their spatial and economic effects. BenDor et al. (2020) emphasize that these effects are often driven by spatial fragmentation, especially a pattern known as "checkerboarding," in which scattered buyouts leave pockets of remaining homes, complicating neighborhood recovery and land reuse.

There have been both stated preference (SP) and revealed preference (RP) studies examining the valuation of floodplain buyouts. Table 1 summarizes key contributions in this literature, organized by author, buyout program, methodology, and findings related to valuation or participation behavior. It also includes indicators of whether each study examined variation in effects by space, time, race, or income. I further elaborate on the studies that explore racial or income heterogeneity in Table 1.1, which is cross-referenced by author and program to align with Table 1. This table provides brief descriptions of how each study addressed race or income.

Two SP studies estimate homeowners’ willingness to pay (WTP) for hypothetical buyout scenarios. Landry et al. (2020) find WTP of $22 per household per year for a North Carolina program, while Ando & Reeser (2022) report WTP of approximately $600 for a pre-flood contract guaranteeing a future buyout. Notably, Ando & Reeser also find that Black residents and higher-income households express stronger preferences for such contracts, raising questions about racial and income disparities in perceived program benefits.

RP studies generally focus on property market impacts. Schoder (2024) estimates that home values increase by about 10% near completed buyouts in a national analysis, with larger effects in lower-income and less-White zip codes. Holloway & BenDor (2023) find average home value gains of $33,407 near buyouts in Mecklenburg County, NC, although benefits decline with distance. Guo et al. (2023) report a 3.7–9% increase in property values near buyouts under New York’s post-Hurricane Sandy program, as well as improved job creation and neighborhood resilience. Hashida & Dundas (2023), using event study and DID methods, also find value gains following acquisitions, though they note these areas tend to be whiter and wealthier.

Other RP work emphasizes cost savings. Nelson & Camp (2020) estimate that buyouts in Tennessee generated $2 billion in avoided structural damages, plus nearly $1 billion in avoided relocation and volunteer labor costs. They also estimate $670,000 in avoided stormwater infrastructure costs. These figures are consistent with FEMA’s required cost-benefit analyses (CBAs), which often show average benefit-cost ratios of 5:1 for buyout programs (BenDor et al., 2020). However, Carran-Groome et al. (2021) note that many CBAs underreport administrative and implementation costs, leading to an incomplete picture of total program expenditures.

Despite these benefits, concerns remain that other flood mitigation policies may unintentionally encourage development in flood-prone areas. Miao & Davlasheridze (2021) argue that subsidized flood insurance under the National Flood Insurance Program (NFIP) reduces incentives to relocate, particularly when payouts are used to rebuild rather than retreat. They also find that counties with higher NFIP enrollment are less likely to participate in buyouts, consistent with underpriced risk dampening demand for relocation.

In addition, there is growing recognition of the distributional and environmental justice dimensions of buyout programs. As summarized in Table 1.1, Jowers et al. (2023) find that Black and Hispanic homeowners receive significantly lower buyout offers relative to their homes’ fair market value compared to White owners. Schoder (2024) shows that while buyout effects on home prices are generally positive, they are weaker in whiter and wealthier areas. Guo et al. (2023) find that mortgage applicants in areas near acquisitions tend to have higher incomes and a greater share of racial minorities after buyouts occur, suggesting demographic shifts that may reflect gentrification. These findings indicate that even when buyouts are economically beneficial on average, their distributional consequences may reinforce existing inequalities.

3. **Data and descriptive statistics**

The first component of my data is the household data. I include housing transactions for all sales in Harris County between [Year 1] and [Year 2], obtained from [source]. The transaction data includes household structural attributes like age and square footage of the household. I merge these data with administrative records from the Harris County Flood Control District (HCFCD) and includes all recorded buyouts under the program from [Year 1] to [Year 2]. This merge produces a dataset of all home sales in Harris County during the study period, with a binary indicator for whether the property was part of a flood buyout.

To incorporate household demographic attributes, I use the Home Mortgage Disclosure Act (HMDA) database, which contains loan-level records including the mortgage applicant’s race, ethnicity, and income. Following the methodology of Lang and VanCeylon (2025), I match HMDA records to property transactions using a combination of sale year, loan amount, and Census tract. This matching process enables me to assign demographic characteristics to a subset of households in the sales dataset.

Neighborhood characteristics are compiled at the Census block level. Using HCFCD GIS shapefiles, I spatially link properties to localized flood risk indicators: base flood elevation, location within the 100- or 500-year floodplain, and distance to bayous and reservoirs. Additional controls include block-level Census demographics, local crime rates, proximity to amenities (e.g., parks, libraries), and school quality. To address potential confounding between flood risk and coastal amenities, I also control for distance to the coastline.

Table 2 presents summary statistics for 3,842 properties included in the HCFCD buyout dataset. Properties span 19 different watersheds and a variety of land use classifications according to the Harris County Appraisal District (HCAD). On average, buyout properties are 0.53 acres in size and cover 33,577.46 square feet. The average year a buyout was initiated is 2007.64, with the process typically concluding in the same year (2007.59 on average). The average appraised land value is $68,564.50, while the average estimated market value is slightly higher at $72,586.57.

To supplement my analysis, I use the Floodplain Property Acquisition (FPA) database developed by Breaux (2022), which compiles information from sources including the Harris County Clerk Real Property Document Search Portal, local government data request portals, and publicly available GIS repositories. This database contains a subsample of 515 observations with verified addresses of where buyout participants relocated. I use this subsample in a robustness check, presented in the appendix. The mean buyout award in this subsample is $254,308.55.

1. **Mechanisms**

When deciding whether to participate in a voluntary buyout program, individuals weigh a complex set of tradeoffs between their current residence and alternative housing options. These considerations are assumed to enter the utility function that describes the benefits a household derives from living in a particular location at a given time. By modeling this utility function, we can estimate preferences and better understand the underlying economic and social factors that drive relocation decisions.

A household’s utility from a residence is influenced by both individual characteristics and external attributes. Personal attributes include income, wealth, age, household size, presence of children, race, education, tenure, risk preferences, life experience, culture, and political affiliation. These factors interact with the characteristics of the buyout program and the new residence. Households consider financial tradeoffs, including the cost of a new home, the broader cost of living in a new location, and the potential opportunity cost of rejecting a buyout—such as future flood damages. Program features like financial assistance, legal support, translation services, and the level of trust in government agencies also affect utility. Trust may depend on the clarity of program outreach, perceived fairness, and the complexity of the application process.

Structural features of the current and prospective homes, such as age, size, and condition, enter into the decision, as do neighborhood characteristics. These include crime rates, school quality, proximity to parks, noise levels, walkability, access to transit, and distance to work or frequently visited places. Flood risk, including both perceived and actual risk, plays a major role. Prior flood experience and access to flood insurance can shape these perceptions, even when buyouts aim to reduce future exposure.

Social and community factors are also important. Proximity to family, friends, and established social networks contributes to the utility of remaining in place. Duration of residence can deepen ties to the local area, enhancing the value of familiarity with local amenities such as stores, parks, or cultural communities. Shared language or cultural background may further increase attachment to the neighborhood.

Relocation imposes frictions, including financial costs such as moving expenses and down payments, time costs associated with paperwork and administrative hurdles, and psychological costs stemming from uncertainty, disruption, and loss of familiarity. The process of adjusting to a new environment can be burdensome, particularly for those with fewer resources or less flexibility. Additionally, peer effects and social influence can shape household behavior. Households may look to the choices and satisfaction of neighbors who have participated in buyouts, and social pressure may play a role in influencing their own decision to accept or reject a buyout.

In contrast to voluntary buyout programs, mandatory buyout programs create fundamentally different decision-making contexts. Rather than opting in, households are informed that their property will be acquired and they must relocate. While they can reject an initial offer, a second rejection triggers acquisition through eminent domain. As such, the utility calculus shifts from whether to participate in a buyout to how households respond to a forced move. In this context, factors such as perceived fairness, available support, and resettlement options become central to shaping utility.

Mandatory buyouts often target low-income, minority, and non-English-speaking communities, raising important environmental justice concerns. Households in these communities may feel disproportionately burdened by relocation, especially if the process is perceived as coercive, rushed, or discriminatory. These perceptions can reduce the utility associated with relocation, even if the move improves housing quality or physical safety. Unlike voluntary programs that rely heavily on federal FEMA funding (which restricts participation by undocumented immigrants), mandatory programs often use local or state funding sources, such as Community Development Block Grants (CDBG). This flexibility allows local governments to offer assistance to undocumented residents, broadening eligibility and potentially increasing the program’s reach and equity.

Mandatory programs also tend to offer more generous relocation assistance and incentives. These often include full coverage of moving and closing costs, housing or rental supplements that exceed federal caps, bonuses for relocating within the county, and the flexibility to transition from mobile homes to more stable single-family housing. The Uniform Relocation Assistance and Real Property Acquisition Policies Act (URA) further ensures that displaced households receive comparable housing with similar amenities, such as the same number of bedrooms. These benefits may increase willingness to participate in a mandatory buyout, particularly among households that face barriers to accessing safer housing options on their own.

To build trust and reduce informational frictions, the Harris County mandatory buyout programs emphasize public communication and resident engagement. Outreach may include town halls, virtual meetings (especially during the COVID-19 pandemic), neighborhood field offices, and dedicated relocation teams, including Spanish-speaking staff. One-on-one meetings with program staff help residents better understand their options and reduce uncertainty. These efforts are particularly important for historically underserved communities that may harbor deep mistrust of government initiatives due to past experiences of neglect or exploitation.

Nonetheless, even with such support, mandatory buyouts still impose costs that shape willingness to participate. Households may suffer the loss of community ties, particularly in tightly knit or culturally homogenous neighborhoods. They may face the psychological cost of leaving a familiar environment or perceive the process as coercive, especially if it disproportionately affects non-English-speaking or minority households. These costs may vary across demographic groups and influence willingness to participate in complex, sometimes conflicting ways. For example, lower-income households may be more likely to participate because of generous financial assistance, yet they may also be more resistant due to fears of displacement or skepticism toward institutional actors.

Even when flood risk is objectively reduced by relocation, the lack of agency inherent in mandatory programs can diminish perceived autonomy. Households that do not understand or trust the policy rationale may feel powerless, decreasing their perceived utility and complicating their response to the buyout offer—even if the program is well-intentioned and designed to promote equity or protect vulnerable populations.

Ultimately, mandatory buyout programs differ significantly from voluntary ones in terms of administration, funding mechanisms, target populations, and implementation practices. These differences affect how households experience the relocation process, how they form preferences over staying versus moving, and how they assess their willingness to pay (WTP) to reduce flood risk through participation in such programs.

**5. Conceptual framework**

I estimate household willingness to accept (WTA) flood risk associated with the voluntary buyout program in Harris County, Texas, using a residential sorting model. Appendix A presents a glossary that defines variables and parameters I present in my conceptual framework and estimation strategy. At each time period *t*, a household 𝑖 chooses a census block 𝑗 from the available set, trading off housing prices and local amenities.

Each block *j* at time *t* has observable characteristics ​, which include housing structure attributes, spatial amenities, flood risk, and sociodemographic variables. These are divided into two groups: which enter utility with homogenous coefficients, and , for which preferences vary across households. Additionally, denotes the housing price index[[1]](#footnote-1) in block 𝑗,and is an indicator variable for proximity to a buyout property. An unobserved block-level component , captures omitted variables. A household’s indirect utility from choosing block *j* is,

(1)

where is an idiosyncratic taste shock.

To allow for preference heterogeneity, the coefficients on and to vary with household characteristics . Preferences for the attribute are represented by , where *k* indexes the race or income group.

Letting represent the mean utility of block 𝑗, I define,

(2) ,

so utility becomes,

(3).

I assume household 𝑖 chooses the block 𝑗 that maximizes their utility from their choice set. Assuming the idiosyncratic utility shocks follows a Type I Extreme Value distribution, the probability that household 𝑖 selects block 𝑗 is,

(4) .

Given movers in period *t*, the predicted market share of block *j* is,

(5) .

Estimation proceeds by setting the predicted shares equal to observed shares in the data and solving for the mean utilities that match observed location patterns.

1. **Estimation**

I adopt the two-stage estimation procedure introduced by Bayer et al. (2007) and applied by Bakkensen and Ma (2020). The first stage recovers the mean utility terms and household-specific preference parameters () using Maximum Likelihood Estimation. In the second stage, I regress the estimated on location attributes and prices to identify the coefficients of interest.

**6.1 Stage 1**

In the first stage, I aggregate the individual probabilities defined in equation (4) to compute the predicted demand for location 𝑗 at time 𝑡

(6) .

Assuming market clearing, predicted demand must equal the observed supply of housing units,

(7)

The parameters are estimated by maximizing the log-likelihood of observed location choices,

(8)

where is an indicator equal to 1 if household *i* chooses location *j* at time *t*. The outer loop of the algorithm searches over household-specific parameters (), while the inner loop solves for the mean utilities that equate the predicted and actual market shares. The likelihood function is maximized to force the sum of predicted probability shares equal to total supply.

To compute I implement the following contraction mapping,

(9) ,

where *c* indexes the iterations. One location in each time period is normalized to have for identification. This process is iterated until the predicted choice shares converge to the observed shares. The result is an estimate of the mean utilities and household-specific preference parameters that best explain the observed residential choices.

**6.2 Stage 2**

In the second stage, I decompose the estimated mean utilities by regressing them on location attributes and housing prices. The model to estimate is,

(10) .

where and are the coefficients representing preferences for the baseline group (households where . However, this regression cannot be estimated consistently via OLS because of endogeneity, since the price index is likely correlated with unobserved neighborhood quality .

To address this, I follow the instrumental variables (IV) strategy used by Berry and Timmins (2007) and Bakkensen and Ma (2020). Their key insight is that prices in a given neighborhood depend not only on its own attributes but also on the characteristics and availability of alternative neighborhoods nearby. In particular, the attributes within a reasonable distance (3-5 km) can influence the equilibrium price of a block without directly affecting the utility of living in that block, conditional on observables.

Therefore, I use the share of undeveloped land in surrounding areas (within 3-5 km) as an instrument for the price index. This satisfies the two IV conditions of relevance and exogeneity. Relevance is satisfied because more undeveloped land nearby affects the supply of housing and therefore local prices. Exogeneity is satisfied since land in nearby areas does not directly enter utility conditional on neighborhood observables.

Rather than estimating equation (10) directly, I use a two-stage least squares (2SLS) strategy. However, this is not a standard 2SLS setup, because in this application, we must also guess and iteratively update the price coefficient . This follows the approach developed by Berry, Levinsohn, and Pakes (1995), where the model must recover both prices and choice shares that are consistent with utility maximization.

To implement this, I rearrange equation (10) by moving price to the left-hand side (LHS) and substituting in a guessed price coefficient . This results in a constructed dependent variable, which allows me to purge the endogenous variation in price with the instrument. This is not a typical first-stage 2SLS because the LHS contains the outcome of interest plus a guessed endogenous term. I then introduce the IV, , the share of undeveloped land nearby, to the right-hand site. The first regression of the 2SLS I estimate is:

(11) .

Estimating (11) produces that is driven only by exogenous variation in prices, meaning we have the utility purged of the endogeneity from the correlation of price and unobservables.

I then estimate a second-stage regression (12), similar equation to (10), but now using the “purged” version of mean utility, denoted as the dependent variable.

(12) .

The tilde (~) indicates that this is the residualized utility from the first-stage regression. The asterisk (\*) indicate the 2SLS estimates of preference parameters that are now free from price endogeneity.

Finally, recall that we started with a guess at Because the price is jointly determined with the market shares in equilibrium, I cannot estimate this in one step. Instead, I follow an iterative process: (1) I start with a guess for . (2) I solve the contraction mapping, using the observed and predicted utilities to recover. (3) Then I estimate equations (11) and (12). (4) I update the guess for based on the new estimates. (5) I repeat steps (2)-(4) until the predicted and observed market shares converge.

1. **Counterfactual Analysis: Welfare Effects of Participating in Buyout Program**
2. **Estimate baseline model over full choice set.**
3. **Compute baseline welfare**
   1. For household i, compute their expected utility in the baseline using the formula,
   2. Probably compensating variation.
4. **Set the counterfactual conditions.**
   1. Change the primitives of interest. I will remove locations that are in the buyout program.
   2. The original choice set all census blocks in Harris County. The new choice set is = , where all census blocks in Harris County that are not part of the flood buyout program.
5. **Initialize variables** so that we have a starting point for the simulation. We need to initialize housing prices and neighborhood sociodemographic composition.
   1. Housing prices
      1. For each neighborhood *j*, start with an initial guess for the price of housing, .
   2. Neighborhood Sociodemographic Composition.
      1. Using data, set the neighborhood level compositions- e.g. % Black, % White, % Hispanic, etc. for each neighborhood *j*.
   3. For example, say we have neighborhoods A, B, and C. They have initial prices A: $200k, B: $180k, C: $220k. And they have initial compositions A: 800 White, 600 Black, 200 Hispanic; B: 300 White, 300 Black, 100 Hispanic; C: 100 White, 600 Black, 800 Hispanic.
6. **Outer Loop**: iterates until sociodemographic compositions converge
   1. **Estimate Utility.**
      1. For each individual i and neighborhood j, compute .
   2. **Compute choice probabilities** 
      1. Using the utility-maximizing choices, calculate the probability they choose each neighborhood with a logit model, .
      2. Suppose for individual 1: ,
   3. **Update neighborhood compositions.** 
      1. This is done by aggregating choice probabilities to the neighborhood level with the formula
      2. For example,

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Person |  |  |  | Sociodemographic characteristic |
| 1 (White) | 0.3 | 0.5 | 0.2 | White |
| 2 (Black) | 0.4 | 0.4 | 0.2 | Black |
| 3 (Hispanic) | 0.2 | 0.1 | 0.7 | Hispanic |

The predicted demographic compositions for neighborhood A would be:

* White = 0.3\*1 + 0.4\*0 + 0.2\* 0 = 0.3
* Black = 0.3\*0 + 0.4\*1 + 0.2\* 0 = 0.4
* Hispanic = 0.3\*0 + 0.4\*0 + 0.2\* 1 = 0.2
* So neighborhood A is 30% White, 40% Black, and 20% Hispanic. You can do the same for B and C.
  1. With updated compositions, move to the inner loop.

1. **Inner Loop**- Calculates market clearing prices
   1. Compute aggregate demand per neighborhood with the formula
      1. For example,

|  |  |  |  |
| --- | --- | --- | --- |
| Person |  |  |  |
| 1 (White) | 0.3 | 0.5 | 0.2 |
| 2 (Black) | 0.4 | 0.4 | 0.2 |
| 3 (Hispanic) | 0.2 | 0.1 | 0.7 |

* For this example, we are also going to assume the supply for each neighborhood is 1.
  1. Adjust prices by comparing housing supply and demand.
     1. If 🡺 raise price.
     2. If 🡺 lower price.
     3. So for this example,
        1. = 0.8 and . Since🡺 lower price
        2. = 1 and . Since🡺 keep price
        3. = 1.1 and. Since🡺 raise price
  2. Repeat (i) – (ii) until This gives the market clearing prices, which are passed to the outer loop.

1. **Check for Composition Convergence.**
   1. With the market clearing prices from the inner loop, the outer loop calculates the compositions, so we are now back in the outer loop. In the outer loop we used the formula In this step, we compare from the current and previous iterations We will keep going back to step 3 until this condition holds true.
2. **Compute Compensating Variation (CV)**
   1. After convergence, compute the welfare,
   2. Then compute CV for each household, . This tells us the income transfer needed to hold household *i*’s
   3. For individual *i,* the compensating variation from a change in the choice set from removing neighborhoods in the buyout program is,

Aggregate this across groups to see distributional effects.

1. **Expected Results and Discussion**

Table 3 presents the expected results for the first and second stages of the analysis. The table is organized into two stages. Stage 2: Homogeneous Preferences captures average preferences for neighborhood attributes. Stage 1: Heterogeneous Preferences, which examines how these preferences vary by race and income.

The estimation proceeds in two stages. In Stage 2, I estimate average preferences for neighborhood characteristics by regressing location-specific mean utility on observed neighborhood attributes. These coefficients capture the overall desirability of features like housing prices, proximity to buyouts, or environmental amenities. The coefficients in this stage reflect the average preferences across all households in the sample. I expect the coefficient on housing price α\_(P )to be negative, reflecting disutility from higher housing costs. A negative price coefficient implies that, on average, higher prices reduce utility and make a neighborhood less attractive to households. The buyout indicator, B\_jt ,captures the utility associated with living near a property sold through the program. I expect B\_jt to be negative, suggesting that properties near buyouts are viewed as less desirable. This may reflect concerns about flood risk, perceptions of neighborhood instability, or stigma associated with areas where buyouts have occurred.

In Stage 1, I estimate heterogeneous preferences by allowing coefficients to vary by race and income. These results are interpreted relative to a baseline group: White and Asian households in the highest income quintile. The interaction terms in this stage reveal how other groups’ preferences differ from this baseline. I expect Black and Hispanic households and lower-income households to exhibit greater sensitivity to price, which would be reflected in a more negative price coefficient relative to the baseline group. This would indicate that these households experience stronger disutility from higher housing costs, potentially due to tighter budget constraints or higher moving costs. I also expect these groups to differ in how they value proximity to buyouts. Specifically, I expect minority and lower-income households to have a less negative coefficient on the buyout indicator, suggesting that they view buyout-adjacent areas more favorably than the baseline group. This should not be interpreted as a preference for flooding risk, but rather as a reflection of constrained choices, greater housing market frictions, or the presence of strong community ties that shape sorting behavior in the face of environmental risks.

1. **Conclusion**

This study has examined how households evaluate neighborhood characteristics, housing prices, and the proximity to buyouts in the context of environmental risks. The results from Stage 2 reveal that proximity to buyouts negatively impacts utility, likely due to concerns about flood risk, neighborhood instability, or stigma associated with areas affected by buyouts. Stage 1, which accounts for heterogeneous preferences by race and income, uncovers important variation in how different groups perceive these risks and opportunities. Specifically, Black, Hispanic, and lower-income households exhibit stronger sensitivity to housing price increases compared to the baseline group of White and Asian households in the highest income quintile. This likely stems from these groups' budget constraints and higher moving costs, as well as housing discrimination. Proximity to buyouts is viewed less negatively by minority and lower-income households than by the baseline group. This does not suggest a preference for flood risk, but rather reflects constrained housing choices and strong community ties, which shape their relocation decisions.

Given these findings, transitioning to mandatory buyout programs could address the inequities and fragmentation caused by voluntary buyouts. A mandatory buyout policy would ensure that all households in vulnerable areas, particularly those who are less likely to participate in voluntary buyouts due to financial or social constraints, have access to relocation assistance. By mandating buyouts in flood-prone areas, policymakers could mitigate the "checkerboard effect," where voluntary buyouts result in fragmented, unstable neighborhoods. This approach would facilitate the creation of contiguous areas of land, promoting stability for long-term recovery or repurposing as greenspace for flood prevention.

In addition, buyout programs should ensure that all households, regardless of income or race, have equal access to relocation assistance, legal support, and language services. Addressing these disparities would not only reduce inequities in flood risk exposure but also promote more equitable outcomes, ensuring that no group is excluded from the process. Broadly, climate adaptation strategies must prioritize equity and justice considerations, particularly in light of historical and current housing discrimination that can lead to gentrification. To prevent the displacement of existing communities, buyout programs should include comprehensive relocation support and mechanisms for community engagement in decision-making.

Ultimately, this study contributes to the growing body of research advocating for a more inclusive and equitable approach to flood risk management and climate adaptation. By understanding the diverse preferences and constraints faced by different populations, policymakers can design strategies that not only protect at-risk communities but also foster resilience in the face of increasingly severe environmental risks.

**References**

1. Bakkensen, L. A., & Ma, L. (2020). Sorting over flood risk and implications for policy reform. Journal of Environmental Economics and Management, 104, 102362. <https://doi.org/10.1016/j.jeem.2020.102362>
2. Barwick, P. J., Li, S., Waxman, A., Wu, J., & Xia, T. (2023). Efficiency and equity impacts of urban transportation policies with equilibrium sorting. Journal of Urban Economics, 135, 103513. <https://doi.org/10.1016/j.jue.2022.103513>
3. Bayer, P., McMillan, R., & Rueben, K. (2001). The causes and consequences of residential segregation: An equilibrium analysis of neighborhood sorting (Working Paper). Yale University.
4. Bayer, P., McMillan, R., & Rueben, K. (2004). An equilibrium model of sorting in an urban housing market (NBER Working Paper No. 10865). National Bureau of Economic Research. https://doi.org/10.3386/w10865
5. Bayer, P., & Timmins, C. (2003). Estimating equilibrium models of sorting across locations (Center Discussion Paper No. 862). Yale University, Economic Growth Center.
6. BenDor, T. K., Salvesen, D., Kamrath, C., & Ganser, B. (2020). Floodplain buyouts and municipal finance. Natural Hazards Review, 21(3), 04020012. <https://doi.org/10.1061/(ASCE)NH.1527-6996.0000380>
7. Berry, S., Levinsohn, J., & Pakes, A. (1995). Automobile prices in market equilibrium. Econometrica, 63(4), 841–890. <https://doi.org/10.2307/2171802>
8. Binder, S. B., Greer, A., & Zavar, E. (2023). Home buyouts: A tool for mitigation or recovery? Emerald Insight.
9. Binner, A., & Day, B. (2017). How property markets determine welfare outcomes: An equilibrium sorting model analysis of local environmental interventions. Environmental and Resource Economics, 69(4), 733–761. https://doi.org/10.1007/s10640-016-0101-8
10. Bonnyman, H. (2024, September 12). Mandatory home buyouts in Houston, Texas: Program overview and lessons learned. New America. <https://www.newamerica.org/future-land-housing/briefs/mandatory-home-buyouts-in-houston/>
11. Cain, L., Hernandez-Cortes, D., Timmins, C., & Weber, P. (2024). Recent findings and methodologies in economics research in environmental justice. Review of Environmental Economics and Policy, 18(1), 116–142.
12. Couture, V., Gaubert, C., Handbury, J., & Hurst, E. (2024). Income growth and the distributional effects of urban spatial sorting. Review of Economic Studies, 91(2), 858–898. https://doi.org/10.1093/restud/rdad048
13. Curran-Groome, W., Haygood, H., Hino, M., BenDor, T. K., & Salvesen, D. (2021). Assessing the full costs of floodplain buyouts. Climatic Change, 168(3), Article 3. <https://doi.org/10.1007/s10584-021-03264-4>
14. Elliott, J. R., & Wang, Z. (2023). Managed retreat: A nationwide study of the local, racially segmented resettlement of homeowners from rising flood risks. Environmental Research Letters, 18(6), 06405. <https://doi.org/10.1088/1748-9326/accfd6>
15. Federal Emergency Management Agency. (2023). Robert T. Stafford Disaster Relief and Emergency Assistance Act. U.S. Department of Homeland Security. https://www.fema.gov/disaster/stafford-act
16. Guo, W., Liao, Y. P., & Miao, Q. (2023). Managed retreat and flood recovery: The local economic impacts of a buyout and acquisition program. Resources for the Future. <https://www.rff.org/publications/working-papers/flood-recovery-local-economic-impacts-of-buyout-and-acquisition-hurricane-sandy-new-york/>
17. Harris County Flood Control District. (2025). About us. <https://www.hcfcd.org/About>
18. Harris Recovery. (2025). Buyout program. <https://www.harrisrecovery.org/Programs/Buyout>
19. Hashida, Y., & Dundas, S. J. (2023). Barriers to coastal managed retreat: Evidence from New Jersey’s Blue Acres program. Marine Resource Economics, 39(3), Article 3. <https://doi.org/10.5325/marineresecon.39.3.001>
20. Holloway, W. P., & BenDor, T. K. (2023). Residential property value impacts of floodplain buyouts in Charlotte, North Carolina. Journal of Environmental Management, 347, 119165. <https://doi.org/10.1016/j.jenvman.2023.119165>
21. Horn, D. P. (2024, May 28). Floodplain buyouts: Federal funding for property acquisition (CRS Insight No. IN11911). Congressional Research Service. https://crsreports.congress.gov/product/pdf/IN/IN11911
22. Jowers, K., Ma, L., & Timmins, C. D. (2023). Racial gaps in federal flood buyout compensations. AEA Papers and Proceedings, 113, 451–455.
23. Klaiber, H. A., & Kuminoff, N. V. (2014). Equilibrium sorting models of land use and residential choice. In J. M. Duke & J. Wu (Eds.), The Oxford Handbook of Land Economics (pp. 352–379). Oxford University Press. <https://doi.org/10.1093/oxfordhb/9780199763740.013.011>
24. Kuminoff, N. V., Smith, V. K., & Timmins, C. (2013). The new economics of equilibrium sorting and policy evaluation using housing markets. Journal of Economic Literature, 51(4), 1007–1062. https://doi.org/10.1257/jel.51.4.1007
25. Landry, C. E., Shonkwiler, J. S., & Whitehead, J. C. (2020). Economic values of coastal erosion management: Joint estimation of use and existence values with recreation demand and contingent valuation data. *Marine Resource Economics*, 28(3), 253-267. <https://doi.org/10.5950/0738-1360-28.3.253>
26. Lang, C., & VanCeylon, J. (2025). Voting with their (left and right) feet: Are homebuyers’ values of neighborhood environmental amenities consistent with their politics? Journal of Environmental Economics and Management, 131, 103157. https://doi.org/10.1016/j.jeem.2024.103157
27. Mach, K. J., Kraan, C. M., Hino, M., Siders, A. R., Johnston, E. M., & Field, C. B. (2019). Managed retreat through voluntary buyouts of flood-prone properties. Science Advances, 5(10), eaax8995. <https://doi.org/10.1126/sciadv.aax8995>
28. Miao, Q., & Davlasheridze, M. (2021). Managed retreat in the face of climate change: Examining factors influencing buyouts of floodplain properties. Natural Hazards Review, 23(1), 1–10. <https://doi.org/10.1061/(ASCE)NH.1527-6996.0000042>
29. Murphy, J. J., & Stevens, T. H. (2016). Contingent valuation, hypothetical bias, and experimental economics. Environmental and Resource Economics, 65(1), 1–16. <https://doi.org/10.1017/S1355770X16000334>
30. Nelson, K. S., & Camp, J. (2020). Quantifying the benefits of home buyouts for mitigating flood damages. Anthropocene, 31, 100246.
31. Siders, A. R., & Gerber-Chavez, L. (2021). Floodplain buyouts: Challenges, practices, and lessons learned. University of Delaware, Institute for Public Administration.

**Tables and Figures**

Tables

*Table 1. Summary of Economic Effects of Flood Buyouts*

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Paper | | | | Type of effects | | | | |
| Authors | Program | Methods | Benefit type | | Spatial | Temporal | Racial | Income |
| Guo et al. (2023) | Hurricane Sandy Acquisition and Buyout | Difference-in-Differences (RP) | Property values, job creation, enhanced resilience | | Yes | Yes | No | No |
| Nelson & Camp (2020) | Tennessee FEMA buyout | FEMA algorithm | Avoided damages, relocation, volunteer labor | | No | No | No | No |
| Ando & Reeser (2022) | Hypothetical Pre-Flood Contract | Contingent Valuation (SP) | Willingness to pay for guaranteed post-flood buyout | | No | No | Yes | Yes |
| Jowers et al. (2023) | Various (1989-2017) | Hedonic (RP) | Difference between FMV and buyout offer across racial groups | | No | No | Yes | No |
| Schoder (2024) | Various (1989-2017) | Propensity Score Weighted DID (RP) | Property value appreciation post-buyout | | No | No | Yes | Yes |
| Holloway & BenDor (2023) | Mecklenburg County, NC Buyout | Hedonic (RP) | Property value appreciation | | Yes | Yes | No | No |
| Hashida & Dundas (2023) | NY Rising Buyout & Acquisition Program | Event Study & Hedonic Repeat Sales DID (RP) | Property value appreciation | | Yes | Yes | No | No |

*Table 1.1 Economic Effects by Race and Income*

|  |  |  |  |
| --- | --- | --- | --- |
| Authors | Program | Race-Related Outcomes | Income-Related Outcomes |
| Guo et al. (2023) | NY Rising Buyout & Acquisition Program | Higher share of racial minorities among mortgage applicants post-buyout nearby | Higher average income among mortgage applicants post-buyout nearby |
| Ando & Reeser (2022) | Hypothetical Pre-Flood Contract | Black residents report higher WTP for buyouts with insurance than other race groups | Higher-income households have higher WTP for buyout programs |
| Jowers et al. (2023) | Various Programs (1989–2017) | Black and Hispanic owners receive lower buyout offers relative to FMV than White owners |  |
| Schoder (2024) | Various Programs (1989–2017) | Buyout effect positive but smaller in predominantly White ZIP codes | Buyout effect higher in lower-income, more rural ZIP codes |
| Hashida & Dundas (2023) | NY Rising Buyout & Acquisition Program | Areas with acquisitions tend to be Whiter | Areas tend to be wealthier, more educated, with more owner-occupied housing |

**Tables**

*Table 2. Summary Statistics for HCFCD Dataset*

|  |  |  |
| --- | --- | --- |
| Variable | Description | Share |
| *Categorical Variables* |  |  |
| *Watershed* | A watershed is a land area that ultimately drains rainfall runoff (or stormwater) to a common body of water. |  |
| *Addicks* Reservoir |  | 0.13% |
| *Armand Bayou* |  | 3.20% |
| *Brays Bayou* |  | 1.98% |
| *Buffalo Bayou* |  | 0.16% |
| *Carpenters Bayou* |  | 0.13% |
| *Cedar Bayou* |  | 0.36% |
| *Clear Creek* |  | 1.93% |
| *Cypress Creek* |  | 11.69% |
| *Greens Bayou* |  | 32.04% |
| *Hunting Bayou* |  | 2.68% |
| *Little Cypress Creek* |  | 0.36% |
| *Luce Bayou* |  | 0.13% |
| *San Jacinto & Galveston Bay* |  | 0.05% |
| *San Jacinto River* |  | 12.40% |
| *Sims Bayou* |  | 0.62% |
| *Spring Creek* |  | 0.03% |
| *Spring Gully & Goose Creek* |  | 0.03% |
| *Vince Bayou* |  | 0.44% |
| *White Oak Bayou* |  | 31.44% |
| *Willow Creek* |  | 0.16% |
| *Land Use ID* | HCAD land use code |  |
| *1000* | Res Vacant Table Value | 24.44% |
| *1001* | Res Improved Table Value | 12.26% |
| *1006* | Condo Land | 0.05% |
| *2000* | Res Vacant Override | 0.16% |
| *2001* | Res Improved Override | 0.21% |
| *2003* | Res Improved Override (Res. Use) | 0.29% |
| *4600* | Vacant Exempt Land | 0.34% |
| *7000* | UDI Vacant Land | 0.03% |
| *8000* | Land Neighborhood General Assignment | 9.63% |
| *8001* | Land Neighborhood Section 1 | 0.05% |
| *8002* | Land Neighborhood Section 2 | 1.22% |
| *8003* | Land Neighborhood Section 3 | 2.73% |
| *8004* | Land Neighborhood Section 4 | 0.86% |
| *8005* | Land Neighborhood Section 5 | 0.03% |
| *Continuous Variables* | Description | Mean |
| *Property Acreage* | Acreage being conveyed | 0.53 |
| *Year Initiated* | Year buyout process began | 2007.64 |
| *Year Finalized* | Year buyout process finished | 2007.59 |
| *Land Square Footage* | Property square footage | 33,577.46 |
| *Appraised Value* | HCAD land value appraisal in dollars | 68,564.50 |
| *Market Value* | Estimated market value of property | 72,586.57 |
| *Observations* | 3842 |  |

*Table 3. Expected Results*

|  |  |  |
| --- | --- | --- |
| Variable | Expected Sign | Rationale |
| **Stage 2: Homogeneous Preferences** |  |  |
| *Housing Price (* | Negative (–) | Higher prices reduce utility |
| *Buyout Proximity (* | Negative (–) | Buyouts may signal flood risk, blight, or instability |
| *Amenity (e.g. bedrooms) )* | Positive (+) | More bedrooms add utility |
| *Amenity: flood elevation* | Negative (–) | Flood risk reduces utility |
| **Stage 1: Heterogeneous Mean utility (** |  |  |
| *Blackck* | Positive (+) | May prefer familiar or constrained by discrimination |
| *x Hispanic* | Positive (+) | Similar reasons |
| *x Lower Income* | Negative (–) | Less location flexibility |
| **Stage 1: Heterogeneous Housing Price** |  |  |
| *Blackck* | Negative (–) | More price-sensitive due to constrained resources |
| *x Hispanic* | Negative (–) | Similar reasons |
| *x Lower Income* | Negative (–) | Similar reasons |
| **Stage 1: Heterogeneous Buyout Proximity** |  |  |
| *Blackck* | Less negative (–) | May value housing availability, community stability |
| *x Hispanic* | Less negative (–) | Similar reasons |
| *x Lower Income* | Less negative (–) | Similar reasons |

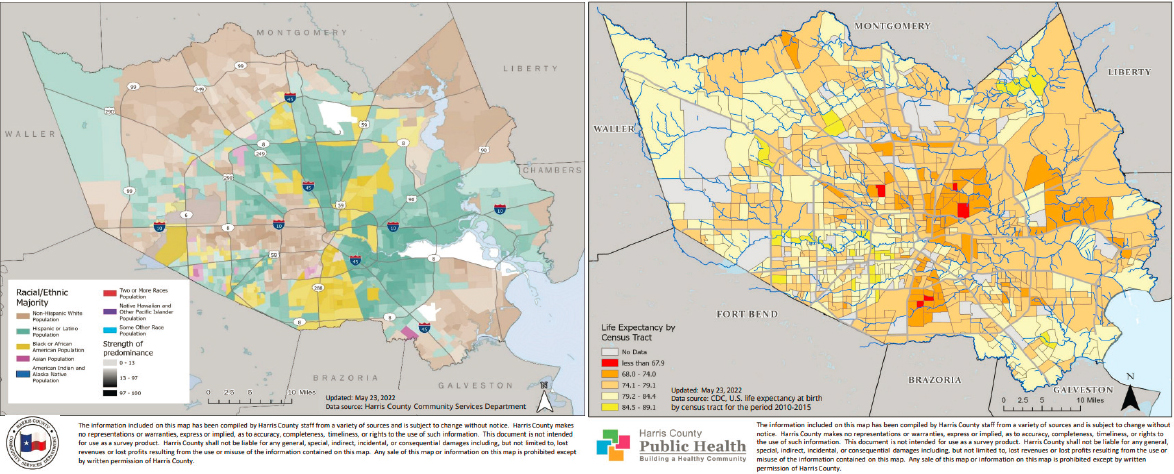
Figures

*Figure 1. Active flood buyouts in Harris County, Texas.*

A map of a large area

AI-generated content may be incorrect.

*Figure 2. Racial and Ethnic Composition of Harris County, Texas.*



Appendices

Appendix A. Glossary

|  |  |
| --- | --- |
| Symbol | Description/Interpretation |
|  | Index for household 𝑖, the individual household choosing a residential location |
|  | Index for census block 𝑗, the residential location chosen by household 𝑖 |
|  | Index for time, the year at which household 𝑖 chooses location 𝑗 |
|  | Index for household demographic variable (e.g., income, race) |
|  | Location attributes with heterogeneous preferences |
|  | Indirect utility of household 𝑖 from choosing block 𝑗 at time 𝑡 |
|  | Mean utility of block 𝑗, accounting for average preferences over common characteristics |
|  | Vector of observable characteristics for block 𝑗 at time 𝑡 |
|  | Vector of observable location attributes with homogeneous preferences |
|  | Vector of attributes with heterogeneous preferences (i.e., interactions with ) |
|  | Cost of living in location j at time t |
|  | Indicator for proximity to a buyout property |
|  | Household demographic characteristics (e.g., income, race) |
|  | Unobserved block-level characteristics (e.g., neighborhood quality) |
|  | Idiosyncratic taste shocks for household 𝑖, assumed to follow a Type I Extreme Value distribution |
|  | Coefficient on that​ captures the average effect of characteristics in on utility. Since these preferences are homogeneous, the effect is the same for all households. |
|  | Coefficient measuring how cost of living affects utility |
|  | Coefficients capturing how average household characteristics affect preferences for |
|  | Average effect of proximity to a buyout property () on utility |
|  | Coefficients capturing how specific demographic variable affects preferences for |
|  | Coefficients capturing how affects preferences for proximity to a buyout property |
|  | Probability household *i* chooses location *j* at time *t* |
|  | Number of movers in period 𝑡 |
|  | Predicted market share of block 𝑗 at time 𝑡 |
|  | Predicted demand for housing in block j at time t |
|  | |  | | --- | |  |   Supply of housing units in block 𝑗 at time 𝑡 |
|  | Observed choice of household 𝑖 at time 𝑡 |
|  | Instrument: share of undeveloped land nearby block 𝑗 |
|  | Estimated mean utility from Stage 1 of 2SLS, used in Stage 2 of 2SLS |
|  | 2SLS estimates of preferences for |
|  | 2SLS estimates of preferences for |
|  | 2SLS estimates of preferences for |

Appendix B. General Equilibrium Counterfactual Analysis Steps.

* + - 1. **Set the counterfactual conditions.**
  1. Change the primitives of interest.
  2. For example, set the preference parameters for racial composition equal to zero to simulate a world where people do not value neighborhood racial composition.
     1. If utility looks like this: . In the counterfactual I will set Then utility under the counterfactual will look like this: .

1. **Initialize variables** so that we have a starting point for the simulation. We need to initialize housing prices and neighborhood sociodemographic composition.
   1. Housing prices
      1. For each neighborhood *j*, start with an initial guess for the price of housing, .
   2. Neighborhood Sociodemographic Composition.
      1. Using data, set the neighborhood level compositions- e.g. % Black, % White, % Hispanic, etc. for each neighborhood *j*.
   3. For example, say we have neighborhoods A, B, and C. They have initial prices A: $200k, B: $180k, C: $220k. And they have initial compositions A: 800 White, 600 Black, 200 Hispanic; B: 300 White, 300 Black, 100 Hispanic; C: 100 White, 600 Black, 800 Hispanic.
2. **Outer Loop**: iterates until sociodemographic compositions converge
   1. **Estimate Utility.**
      1. For each individual i and neighborhood j, compute .
   2. **Compute choice probabilities** 
      1. Using the utility-maximizing choices, calculate the probability they choose each neighborhood with a logit model, .
      2. Suppose for individual 1: ,
   3. **Update neighborhood compositions.** 
      1. This is done by aggregating choice probabilities to the neighborhood level with the formula
      2. For example,

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Person |  |  |  | Sociodemographic characteristic |
| 1 (White) | 0.3 | 0.5 | 0.2 | White |
| 2 (Black) | 0.4 | 0.4 | 0.2 | Black |
| 3 (Hispanic) | 0.2 | 0.1 | 0.7 | Hispanic |

The predicted demographic compositions for neighborhood A would be:

* White = 0.3\*1 + 0.4\*0 + 0.2\* 0 = 0.3
* Black = 0.3\*0 + 0.4\*1 + 0.2\* 0 = 0.4
* Hispanic = 0.3\*0 + 0.4\*0 + 0.2\* 1 = 0.2
* So neighborhood A is 30% White, 40% Black, and 20% Hispanic. You can do the same for B and C.
  1. With updated compositions, move to the inner loop.

1. **Inner Loop**- Calculates market clearing prices
   1. Compute aggregate demand per neighborhood with the formula
      1. For example,

|  |  |  |  |
| --- | --- | --- | --- |
| Person |  |  |  |
| 1 (White) | 0.3 | 0.5 | 0.2 |
| 2 (Black) | 0.4 | 0.4 | 0.2 |
| 3 (Hispanic) | 0.2 | 0.1 | 0.7 |

* For this example, we are also going to assume the supply for each neighborhood is 1.
  1. Adjust prices by comparing housing supply and demand.
     1. If 🡺 raise price.
     2. If 🡺 lower price.
     3. So for this example,
        1. = 0.8 and . Since🡺 lower price
        2. = 1 and . Since🡺 keep price
        3. = 1.1 and. Since🡺 raise price
  2. Repeat (i) – (ii) until This gives the market clearing prices, which are passed to the outer loop.

1. **Check for Composition Convergence.**
   1. With the market clearing prices from the inner loop, the outer loop calculates the compositions, so we are now back in the outer loop. In the outer loop we used the formula In this step, we compare from the current and previous iterations We will keep going back to step 3 until this condition holds true.

Appendix C. Robustness Check using Destination Subsample

Appendix D. Instrumental Variable (IV) Robustness Checks.

1. I follow Lang and VanCeylon (2025) and regress log sale price on housing characteristics and year and location fixed effects. The estimated location fixed effects, which net out structural quality, are converted to dollar values and annualized using a 7.5% capitalization rate (Costa and Kahn, 2003) to create the quality-adjusted price index used in the sorting model. [↑](#footnote-ref-1)