Residential Sorting and the Economic Effects of Flood Buyout Programs

A prospectus chapter by Emma Donnelly

Abstract

1. **Introduction**

Flooding is one of the most damaging and costly consequences of climate change, increasingly threatening infrastructure, homes, and entire communities. As the intensity and frequency of flood events rise, governments have turned to managed retreat—most often in the form of flood buyout programs—as a strategy to reduce long-term risk. These programs typically involve government agencies purchasing homes from voluntary participants in flood-prone areas, compensating them to relocate to safer locations. The acquired properties are usually converted into open or green spaces, preventing future damage and offering ecosystem benefits. Over the past two decades, the number of U.S. homes sustaining repeated flood damage has nearly doubled, reaching around 229,000. To date, more than 1,100 local governments across 49 states have implemented voluntary property acquisition programs (Siders, 2021).

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. This study proposes a residential sorting model to estimate households’ willingness to pay (WTP) to avoid flood risk through participation in voluntary flood buyout programs. My research question is: *What are people willing to pay to avoid flood risk through participating in flood buyout programs?* I hypothesize that WTP is positive and significant.

While prior research shows the economic benefits of flood buyout programs using hedonic analysis and contingent valuation methods (Guo, 2023; Nelson, 2020; Ando, 2022; Jowers, 2023; Bonnyman, 2024; Holloway, 2023; Hashida, 2023) this is the first study I know of to apply a residential sorting model framework to this policy context. Sorting models offer several advantages over traditional hedonic methods. While hedonic models are often subject to omitted variable bias due to unobserved neighborhood characteristics, sorting models incorporate both observed and unobserved location-specific factors—often through the use of instrumental variables—allowing for more accurate estimation of WTP. They are well-suited for evaluating non-marginal changes, such as large-scale policy interventions that alter residential patterns, housing prices, and local amenities. Additionally, sorting models can disaggregate welfare impacts by demographic and socioeconomic groups, providing insights into the equity implications of buyouts. They also better account for endogenous amenities and sorting dynamics that may bias hedonic estimates of capitalization effects, thereby yielding more credible estimates of how households value environmental risk reduction.

Harris County, Texas, offers a valuable case for this analysis. 3,500 properties have been purchased through the program, making it the program with the highest number of buyouts in the US. Its voluntary flood buyout program has operated since 1985 and is among the most active in the United States. A hedonic model would be limited in this setting, as it cannot capture how households sort across neighborhoods in response to changing flood risk. By contrast, the sorting model allows for a richer analysis of heterogeneous responses to both flood exposure and buyout availability.

Accurately estimating WTP in this context is further complicated by the fact that flood-prone areas often coincide with highly desirable coastal amenities, making flood risk negatively correlated with utility-enhancing features (Bakkensen & Ma, 2020). The sorting framework directly models household decision-making, controlling for unobserved preferences and enabling cleaner identification. To address endogeneity concerns, I employ an instrumental variable strategy and control for spatial amenity correlations using distance-to-coast bins.

This study uses novel data from the Harris County Flood Control District (HCFCD) which detailed records on over 3,800 buyout properties across 19 watersheds in Harris County, Texas, along with spatial data identifying the exact location of each property. I combine this with housing transaction data, floodplain information, and neighborhood characteristics to estimate how homeowners value avoided flood risk. A supplemental dataset containing relocation addresses for a subset of buyout participants is used in robustness checks.

This study is important because policymakers are increasingly concerned with how individuals relocate in response to natural disasters. Residential patterns have substantial implications for local economies, and understanding whether people sort across areas with varying disaster risks can inform more effective policy design. Flood buyout programs are costly, making it essential to quantify their benefits. These programs can prevent future damages and reduce public expenditures on disaster recovery. According to the National Institute of Building Sciences, buyouts yield an estimated $5 to $9 in benefits for every $1 spent (Siders, 2021).

1. **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.

The final component of the data includes neighborhood characteristics, compiled at the Census block level. Using GIS shapefiles provided by HCFCD, I spatially link each property to localized flood risk indicators, including base flood elevation, location within the 100-year or 500-year floodplain, and distance to bayous and reservoirs. I also incorporate additional neighborhood-level attributes such as block-level Census demographics (race, income, tenure, and language), local crime rates, proximity to amenities (e.g., parks, libraries), and school quality measures. As flood risk and coastal access may be jointly correlated with housing demand, I also include distance to the coastline as a control.

Table 1 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. **Theoretical/conceptual framework**

**3.1 Sorting Model for the Effect of Locating Near a Buyout**

I estimate household willingness to pay (WTP) for changes in flood risk associated with the voluntary buyout program in Harris County, Texas using a residential sorting. A household’s indirect utility from choosing block time *t* depends on the characteristics of the block and the price of housing. Let the choice set at time *t* be denoted by , which may not be the same each year and for all individuals.

At each time period *t,* a household *i* chooses to locate in census block *j,* trading off various block-level attributes and prices. The observable characteristics of a block *j* at time *t*, denoted ​. We assume households have homogenous preferences over , which include housing structure attributes, spatial amenities, proximity to the coast, flood risk, and neighborhood sociodemographic variables. A second subset of attributes, are the attributes for which we allow households to have heterogeneous preferences. This includes population density, race shares, and income shares of each block. In addition to these observed factors, there is an unobserved component , which captures block-level attributes not directly measured in the data. A household derives utility from choosing block *j*,

(1)

where is the price index[[1]](#footnote-1) of housing in block *j* at time *t* and is an indicator for whether block 𝑗 near a property sold through the buyout program (). The term captures idiosyncratic shocks to household *i*'s utility for block *j*.

To allow for heterogeneous preferences across households, I allow the coefficients on and to vary with household characteristics . Preferences for the attribute are represented by , which allows preferences to differ by race and income.

I express utility as the sum of a mean utility shared by everyone in that block and the idiosyncratic component unique to each household,

(2).

where . The term represents the mean utility of location 𝑗 for a baseline household. Substituting these expressions into the utility function, we can rewrite utility as

(3).

Households are assumed to choose the block that yields the highest utility. Household *i* selects block *j* in period *t* if

(3) if .

Assuming the idiosyncratic utility shocks are independently and identically distributed with a Type I Extreme Value distribution, the probability that household *i* chooses block *j* at time *t* takes the logit form,

(4) .

Given a set of movers in period *t*, the predicted share of movers selecting block *j* is then,

(5) .

I assume in estimation that the predicted market shares ​ equal the observed shares in the data. This moment condition allows us to estimate the vector of mean utilities such that the model reproduces actual location choice patterns.

1. **Estimation**

I adopt the two-stage estimation procedure outlined by Bayer et al. (2007) and Bakkensen and Ma (2020).

In the first stage, I estimate the terms and household specific preference parameters () using Maximum Likelihood Estimation. Following Berry (1994), I implement a contraction mapping routine to estimate the vector of that equates the predicted choice shares of households to locations to the observed choice shares in the data.

I normalize one location’s utility in each time period to zero. The algorithm iterates until the predicted shares from the logit model converge to the observed shares in the data. The likelihood function for the observed choices is,

(6)

where is an indicator equal to 1 if household *i* chooses block *j* at time *t*. The outer loop varies heterogeneous choice shares to recover household-specific parameter estimates .

With the estimated mean utilities from the first stage, I estimate the following linear regression to recover the base group preferences for block-level characteristics,

(8) .

where and are the coefficients representing the preferences of the baseline group (households where .

Because housing prices may be endogenous, potentially correlated with unobserved neighborhood quality, I account for endogeneity of housing prices by instrumenting. I address this concern using an instrumental variables strategy inspired by Bayer and Timmins (2007). I use the share of undeveloped land in surrounding areas within a 3–5-kilometer radius as an instrument for local housing prices. This works as an IV because I assume that characteristics of more distant areas affect local prices, but do not directly influence the utility of a particular block.

To implement the IV strategy, I start with an initial guess for the price coefficient and adjust the estimated mean utility as shown in equation (8),

(8) ,

where is the instrumental variable. I regress the adjusted mean utilities on the neighborhood characteristics and the instrument. This procedure is iterated with updated guesses for until *j* the predicted choice probabilities, using the adjusted utilities, converge to the observed market shares.

1. **Expected Results and Discussion**

In Stage 2, I estimate the average preferences of the baseline for location characteristics. These coefficients reflect the utility associated with observed block-level attributes for the representative household. The parameter of interest in my model is the coefficient on the buyout indicator which equals one if block *j* is near a household that sold their home through the flood buyout program. This parameter captures the average utility associated with living near a home sold through the buyout.

For the baseline household, I expect the coefficient on to be negative, checkerboard effect. I also allow for heterogeneous preferences for buyout participation by household race and income in stage 1. I expect lower-income households to . I expect Black and Hispanic households to

1. **Summary and conclusion**
2. **References**

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and the buyout value of the home.

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**Tables**

*Table 1. 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 2 Sorting Model Results with Homogeneous Preferences

|  |  |
| --- | --- |
| Group | Mean Utility |
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1. Title x

2. Abstract

3. Introduction

4. Theoretical/conceptual framework

5. Empirical framework

6. Data and descriptive statistics

7. (Expected) Results and discussion

8. Summary and conclusion

9. References

10. Plan for communicating results (journal outlets, meetings presentations, popular press)

The order and content of items 4-6 may vary depending on research type (e.g., theory vs

applied) and personal taste. The proposal should be double-spaced with 12 point font

with 1 inch margins. The proposal should be no longer than 10 pages excluding the title

page and references

1. I follow Land 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)