Managed retreat in the face of climate change: What influences buyouts of floodplain properties

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1. Introduction

Flooding is one of the most prevalent and costliest natural disasters in the US (Wing et al. 2020). While its occurrence is often triggered by torrential rainfall or storms, flood-induced damages are heavily influenced by the pattern of human settlement, land-use decisions, and protective systems (e.g., Pielke & Downton, 2000; Miao, 2018). Adaptation to flooding risks involves structural protection (e.g., seawalls, dikes, and levees) and nonstructural measures including relocation and retreat, restricting development in high-risk areas through land use and zoning policy, and enforcing building codes (Kousky, 2014). Relocation and retreat are often a preferred long-term hazard mitigation strategy in flood-prone areas where structural protection alone is deemed insufficient for addressing repetitive flooding losses (de Vries and Fraser, 2012; Zaver and Hagelman, 2016). Managed retreat is also an essential strategy for adapting to climate change, sea-level rise, hurricanes and storm surge (Kousky, 2014; Marino, 2018; Craig, 2019).

The U.S. government has a history of purchasing properties located in hazardous areas that date back to the 1970s (Siders, 2019). Government-sponsored retreat through floodplain buyouts has become a common flood management policy since the great Midwestern flood of 1993 (Pinter, 2005). It is estimated that the U.S. Federal Emergency Management Agency (FEMA)

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funded more than 43,000 buyouts of flood-prone properties between 1989 and 2017 (Mach et al. 2019). These buyouts are primarily funded by federal agencies, with a minimum cost-share requirement for the state and local governments. In a typical buyout project, property owners voluntarily agree to sell their properties to the government at the pre-disaster market price and relocate permanently. Following the acquisition, properties are demolished, and the land is converted into open space in perpetuity.

Despite the financial support of the federal government, buyout programs are often laden with numerous social, economic, and political challenges at the local level (Freudenberg et al. 2016). For homeowners, whether or not to participate in buyouts is a hard decision because government acquisition takes time, and they may find it difficult to find affordable housing nearby. Buyouts also raise concerns for local governments, because relocation may cause a loss of property tax revenues and it also costs governments to maintain the buyout sites (BenDor et al. 2020). In fact, property buyouts are largely a local decision driven by local governments and stakeholders, and, therefore, complicated by their limited capacity and resources as well as the mixed incentives created by federal disaster policies. As noted by Burby (2006), local government officials often pay insufficient attention to disaster mitigation. Furthermore, federal policies that fund public protection works and provide subsidized flood insurance and disaster relief have created the perverse incentive for development in flood-prone areas, thereby increasing future risks of flooding losses (Burby, 2006). This observation elucidates the intergovernmental challenge in disaster risk management in the U.S. federal system (Wildasin 2008; Miao et al. 2020).

In this study, we empirically examine the factors associated with floodplain property acquisitions (measured in the number of bought-out properties and buyout spending) across U.S. counties. We consider buyouts as a joint decision made by households and governments and explore the factors that influence their incentives to engage in buyouts, including a county's fiscal resources and institutions, flooding experiences and exposure, and flood management practices. Our empirical analysis focuses on FEMA's Hazard Mitigation Grant Program (HMGP), which is the primary source of federal buyout funding. We combine data on buyout projects funded through HMGP with data measuring various county characteristics to construct a nation-wide longitudinal dataset spanning the years 1990 to 2016.

Our research contributes to the literature on government buyouts and flood management in several ways. While recent studies have examined the determinants of individual homeowners' decisions about buyouts (e.g., Fraser, 2003; Fraser et al. 2006; Kates et al. 2006; Kick et al. 2011; de Vries and Fraser 2012; Binder et al. 2015; Binder and Greer 2016), less is known about how local government institutions and locality characteristics influence buyout outcomes (Mach et al, 2019). In this study, we focus on the role of local fiscal institutions, considering that buyouts-induced residents' relocation may cause a loss of tax revenues. Specifically, we examine whether a local government is more likely to support buyouts in its community if it has a larger tax base, and is less reliant on property taxes for funding local public services.

Second, we examine the impact of other flood risk management strategies on buyouts with a particular focus on flood insurance provided through the National Flood Insurance Program (NFIP) and local flood protection infrastructure (e.g., levees and dikes). Notably, many scholars have argued that subsidized flood insurance would induce more development in floodplains, yet there is little empirical evidence to support this claim (Kousky, 2019). Our research takes a distinctive perspective to examine the effect of flood insurance uptake on property buyouts and managed retreat as an important land use decision. Our study further extends the disaster management literature by testing the "levee effect" hypothesis, that is, structural protection such as levees might promote a false sense of security, and therefore reduce the incentive for taking other risk mitigation measures such as retreat and relocation (Stefanovic, 2003). Overall, this paper is one of the first studies that investigate the drivers and barriers to government floodplain buyouts at the community level. Our findings not only shed light on the geographic pattern of managed retreat across the U.S. but also provide insights into the key challenges for government buyouts as a climate adaptation strategy.

2. Policy Background and Relevant Literature

2.1 The Hazard Mitigation Grant Program and Government Buyouts

The U.S. federal government has established various policy programs for assisting state and local governments in reducing flood risks. FEMA administers three major hazard mitigation grant programs including HMGP, the Pre-Disaster Mitigation Grant Program, and the Flood Mitigation Assistance Grant Program. All three programs focus on reducing or eliminating long-term risks from future disasters, and, among all, HMGP has funded most of the property buyouts.

Authorized under Section 404 of the 1988 Stafford Act, HMGP provides grants to state, local and tribal governments only after a major disaster declaration is issued by the President (Carter et al. 2018). The goal is to ensure that post-disaster reconstruction and recovery incorporates long-term hazard mitigation measures. While grants are triggered by a Presidential disaster declaration (PDD), the program sometimes makes its funds available statewide in the state that received a PDD and not limited to only declared counties (Carter et al. 2018). A typical HGMP grant covers up to 75 percent of the eligible project costs, with the remainder being provided by state and local governments.[3]

[3] In some cases, local governments can use funds from the Department of Housing and Urban's Development Community Development Block Grant (CDBG) or CDBG-DR programs to cover the nonfederal match.

HMGP funds a variety of mitigation projects including buyouts, stormwater management, structural elevation, floodproof and retrofit, flood control structures, warning systems, mitigation planning, and public education activities. Among all, buyouts or property acquisitions are the largest spending category according to FEMA's data. We estimated that HMGP-funded buyouts in the years 1990-2016 cost approximately $4.7 billion (at 2015 price), accounting for 26 percent of the total HMGP project costs.

A notable feature of government-funded property buyouts is that that individual property owners do not apply directly to FEMA to request government requisition of their properties. Homeowners have to rather apply through state agencies, tribal agencies, and local governments, who can submit grant applications to federal agencies. Local government officials often have significant discretion in administering buyout projects and determining which homeowners are eligible for buyouts. Federal funding guidelines recommend that local program administrators designate priority acquisition areas and target residents within those areas for buyouts. The design and implementation of buyout programs vary substantially by states and local jurisdictions (Freudenberg et al. 2016). Previous research suggests that different buyout programs reflect distinctive objectives and features (Greer and Binder, 2016), and their program design strongly influences participants' buyout experiences (Binder and Greer, 2016). But in all cases, homeowners' participation in government buyouts are voluntary, and they are paid at preflood fair market values for their properties regardless of the disaster damages.

While government buyouts are a common flood management policy in the U.S., the literature on this topic has been limited (Siders et al., 2019). From a theoretical perspective, Kousky (2014) argues that private agents fail to invest in the optimal level of retreat because property owners do not bear the full cost of their location decisions due to publicly-funded protective infrastructure and government disaster aid. They also lack appropriate information about local disaster risks or have biased risk perceptions. These observations suggest that retreat should not be left to the private market alone, which, therefore, justifies policy interventions including buyout programs to incentivize managed retreat from hazard-prone areas.

The existing empirical literature has primarily focused on the factors that influence homeowners' decisions to participate in government buyouts (e.g., Binder et al. 2015; Fraser et al. 2006; Kates et al. 2006; Kick et al. 2011; Greer and Binder 2017). Many of these studies, using survey data or interviews, found that homeowners are more likely to participate in buyout programs when they have experienced greater flood damages, perceive higher future risks, have less attachment to their communities, face larger financial incentives, or report higher trust in or support from local public officials and buyout administration staff. Other research finds substantial variations in homeowners' experiences with buyouts and their sense of voluntariness (de Vries and Fraser, 2012). Recent studies also examined the social equity issue involved in the buyout process and outcomes (e.g., Siders, 2019; de Vries and Fraser 2012; Elliott et al. 2020; McGhee et al. 2020), costs and benefits of buyouts (e.g., Tate et al. 2016; Johnson et al. 2019), and the post-buyout impacts on participating households, land use, and government finance (McGhee et al. 2020; Zavar and Hagelman, 2016; BenDor et al. 2020).

In a recent study that is similar to our research, Mach et al. (2019) examine government buyouts of flood-prone properties in the U.S. from 1989 to 2017. They find that more voluntary buyouts have occurred in counties with higher income and population. Using more detailed zip code-level data, they show that more bought-out properties are located in communities with greater socioeconomic vulnerability as indicated by lower income levels, lower population density, lower education levels, and greater racial diversity. Our paper draws upon Mach et al.

(2019) but explores buyout determinants beyond a community's socioeconomic and demographic characteristics. Specifically, we note that little empirical work has examined how local governments make decisions related to buyouts despite their critical role in administering buyout programs (Siders, 2019; Dyckman et al. 2014). Notably, fiscal constraints are an important factor in local government decision-making. Particularly, buyouts may impose different costs upon localities including direct costs of buyouts, its potential effect on property tax revenues and local economy, and the ability of housing markets to accommodate displaced homeowners (Siders, 2019). There is also anecdotal evidence suggesting local concerns with the potential tax revenue losses due to buyouts (Zavar and Hagelman 2016), though its actual fiscal impact depends on other factors such as where the buyout participants are relocated (BenDor et al. 2020). We expect that adequate financial resource is one enabling factor in local government buyout decisions. Considering that property taxes are the major source of revenues for most U.S. local jurisdictions, buyout-induced relocation may bring a non-negligible loss of local revenues, and this concern would discourage local governments from engaging in buyouts. In this context, we hypothesize that a community would support more property buyouts if it has a larger tax base and is less reliant on property taxes for financing local public services.

2.2. The National Flood Insurance Program (NFIP)

The NFIP was established by the federal government as part of the 1968 National Flood Insurance Act to address the growing cost of flooding and the unavailability of flood insurance in the private insurance market. Communities voluntarily participate in the NFIP to help their residents gain access to flood insurance and, in exchange, they must adopt minimum flood management regulations. The NFIP develops flood insurance rate maps (FIRM) for participating communities, in which areas with a one percent annual chance of flooding, known as the 100-

year floodplain, are identified as the special flood hazard area (SFHA). Homeowners from NFIP participating communities and with properties located in the SFHA are required to purchase flood insurance for receiving a federally-backed mortgage. As of 2019, more than 22,000 communities participated in NFIP, and the program provided over 5 million flood insurance policies and over $1.3 trillion in coverage (CRS, 2019).

The NFIP sets the premium rates for most policies based on the community flood zone maps and hydrological modeling, which are supposed to reflect the true flood risks. However, homes built before the community's first FIRM was completed are eligible for subsidized rates, and about 13 percent of NFIP policies received a pre-FIRM subsidy (CRS, 2019). It has been long observed that the NFIP fails to price its premiums actuarially and ignores the regional heterogeneity of flood exposure (Kousky, 2019). There are also growing concerns that the subsidized flood insurance induces more development in floodplains and undermine other hazard mitigation efforts (e.g., Bagstad et al. 2006; Browne et al, 2018; Craig, 2019). Nonetheless, existing empirical research offers limited evidence to support this claim (Kousky, 2019; Lamond et al. 2009).

Drawing on this strand of literature, we expect that uptake of flood insurance, as a risk transfer strategy, may crowd out investments in *ex ante* risk mitigation. That is because with insurance coverage homeowners do not bear the full cost of damages once an inundation occurs, and would have a lower incentive to relocate from floodplains as a means of reducing their future exposure. Therefore, we hypothesize that a county with higher NFIP take-up rates has fewer government buyouts of flood-prone properties. We also consider the perverse incentive effect of flood insurance, that is, underpriced flood insurance lowers the cost of living in risky locations and may distort the incentive to engage in retreat and relocation. We hypothesize that counties with lower insurance premiums have fewer floodplain buyouts.

In addition to flood insurance, existing flood control infrastructure (e.g., levees and dams) also has the potential to crowd out other efforts to reduce risks by promoting a false sense of security, known as the "levee effect" (Stefanovic, 2003). Previous research has suggested that protective structures encourage more development in floodplains and substantially increase the risk of catastrophic damages (Burby, 2006). Boustan et al. (2012) examined disaster-induced migration across the U.S. counties and found that floods led to net in-migration, which could be due to the increased investment in protective infrastructure following significant flooding events. A similar pattern was also found in the case study of Yuba County, California, where a high population growth occurred following the extension of local levee systems (Hutton et al. 2018). Drawing upon this strand of literature, we hypothesize that counties with more structural protection engage in fewer buyouts of flood-prone properties.

3. Data

For our empirical analysis, we compiled the data from various sources. First, for our dependent variable, we obtained buyouts data from two separate OpenFEMA datasets of HMGP grant projects and hazard mitigation assistance mitigated properties. Based on the project type of each entry, we identified the HMGP-funded property acquisition projects and created two measures, the buyout project costs and the number of bought-out properties in a county. FEMA's raw data link each of the grant projects with a unique PDD disaster number. Using the unique PDD numbers we merged the buyouts data with FEMA's PDD dataset to identify the year and the type of disaster incidents. Note that we used the year in which a PDD occurs to organize our buyouts data instead of the year a buyout project was completed, considering that government acquisition of properties takes multiple years to complete in the aftermath of a major disaster event.

Our national sample includes HMGP-funded property buyouts following all flood-related PDDs (floods, hurricanes, severe storms, and coastal storms) that occurred in the years 1990-2016. We do not include government buyouts triggered by non-flood PDDs. Given that in some cases the HMGP funds are made available to all counties (not only those receiving PDDs) within a state, we included a county observation as long as the county was eligible for HMGP funding in a given year, even if it did not receive a PDD designation in that year. We do not include counties that were ineligible for HMGP funding (i.e., with no PDD designations or no statewide funding eligibility). Finally, we aggregated the buyout project data at the county-year level. Our data show that nearly 2,500 counties had received HMGP funds over the 1990-2016 period and, among them, 948 counties undertook buyouts of properties following a flood or storm PDD. The top five counties in terms of the cumulative buyout project costs are the Harries County (Texas), Bronx County (New York), Galveston County (Texas), Middlesex County (New Jersey), and Cook County (Illinois). We provide more details about the spatial distribution of buyout projects in the online appendix.

For the independent variables, we collected data on a county's flooding shocks, fiscal resources, flood insurance take-ups, protective structures, and other socioeconomic, demographic, and political characteristics. First, to capture contemporaneous flooding shocks, we used FEMA's data to create a variable measuring the number of flood-related PDDs received by a county in a given year. To better capture the magnitude of flooding, we used the precipitation data from the National Climate Data Center (NCDC) Global Historical Climatology Network (GHCN) and constructed a rainfall anomaly variable measuring the proportional deviation of a county's annual precipitation in a year from its long-run average in years 1950-2000 (Davlasheridze and Miao, 2019). A positive value indicates excessive rainfall and possible flooding conditions in a county year. Considering that buyouts may also be motivated by recent flooding events, we included another variable measuring the number of flood-related PDDs in a county in the past three years. Accounting for recent disaster shocks is important for our modeling because they influence not only buyouts but also decisions related to flood insurance purchases. Recent research (Gallagher, 2014; Davlasheridze and Miao, 2019) suggests that floods lead to a temporary increase in flood insurance take-up rates in the following years.[4] We constructed two additional variables to control for a county's long-term flood exposure and risks. The first is the percentage of a country's 100-year floodplains (i.e., SFHA on FEMA's Flood Insurance Rate Map) of its total land area, which was calculated using the spatial data drawn from FEMA's National Flood Hazard Layer. The second is a binary variable indicating a coastal county based on the Census definition (i.e., adjacent to either coastal water or territorial sea).

We constructed two variables for testing our hypotheses related to the effect of local government fiscal resources, using the data from the U.S. Census Bureau's State and Local Government Finance section. The first variable measures a county's total property tax revenues, and the second one is the ratio of a county's property tax revenues to its total public expenditure as a proxy for its fiscal reliance on property taxes. Because most U.S. county governments report their financial data to Census every five years, we linearly interpolated total government expenditures and property tax revenues for the missing years.

[4] We choose the past three years because the disaster literature overall suggests more recent shocks have greater effects on risk mitigation behaviors and insurance purchases. We have conducted sensitivity analysis using alternative 5-year and 10-year spans and found the past three years have a stronger explanatory power.

As for flood insurance, we measure the insurance take-up rates using the total number of policies per capita (residential policies only) for all NFIP participating counties. We also measure a county's average premium (as the sum of premiums divided by total coverage in $1,000) to capture the price of flood insurance and local flooding risks. The flood insurance data are obtained from FEMA through a Freedom of Information Act (FOIA) request. To account for the availability and extent of structural protection, we collected the spatial data from the U.S. Army Corps of Engineers' (USACE) National Levee Database (NLD) and intersected them with the county boundary layer. Using the NLD's reported protected land area for each structure, we calculated the percentage of a county's land area protected by flood control infrastructure.[5]

For other control variables, we collected the per capita income data from the U.S. Bureau of Economic Analysis, unemployment rate data from the Bureau of Labor Statistics, and data on poverty rates from the Census. We obtained data on a county's housing price index (HPI) from the Federal Housing Finance Agency to account for the effect of housing values on buyout decisions. We used the population data from the National Center for Health Statistics to create additional variables measuring a county's percentage of the black population, percentage of people who are at least 65 years old, and population sizes. We also included a population density variable measured as the total population divided by land area. To control for the demand for land development, we used the Internal Revenue Service's population migration database to create a net in-migration variable (total inflows minus outflows). A county's political leaning is measured by the percentage of people voting for a Democratic candidate in the most recent Presidential election, using the data from Dave Leip's Atlas of Presidential Elections.

[5] However, we do note that the NLD data do not include all levees and dams in a county.

Finally, all monetary variables including buyout project costs, tax revenues, and incomes are converted to the 2015 real price. Table 1 summarizes the descriptive statistics of our main variables in the regression sample.

[Table 1 about here]

4. Model

Conceptually, we expect floodplain buyouts to occur when their benefits exceed costs for both local governments and households. Buyouts deliver benefits primarily in the form of future disaster loss avoidance, which should be greater in localities with more severe flood risks and exposure. Recent disaster shocks may also motivate buyouts when they trigger PDDs and raise greater public risk awareness. As discussed above, buyouts impose various direct and indirect costs upon local governments (including a potential loss of tax revenues due to residents' relocation), which deter local government decisions for buyouts. For households, if they rely on other risk transfer strategies such as flood insurance or public protective infrastructure, they may anticipate lower private costs of future flooding, which render buyouts and relocation a less appealing option for them. In addition to the factors of our interest, a community's demand for buyouts can also be influenced by its socioeconomic and demographic characteristics and political leaning.

For the empirical analysis, we combined different datasets aforementioned into an unbalanced panel dataset with the panel unit c indexing counties and t indexing PDD years. Our dependent variable Y_{ct} is either total buyout project costs or the number of bought-out properties in a county c triggered by PDDs that occurred in year t. Since Y_{ct} takes on a zero value with positive probability but is a continuous variable with strictly positive values (for $Y_{ct} > 0$), we use a corner solution model to deal with this type of limited dependent variable. Specifically, we define the latent buyout outcome as Y_{ct}^{*} as a function of the explanatory variables discussed above in the following equations.

(1) $Y_{ct}^{*} = \beta_1 Fiscal_{ct\text{-}1} + \beta_2 NFIP_{ct\text{-}1} + \beta_3 Levee_c + \beta_4 Flood_{ct} + \lambda_t + S_c + \varepsilon_{ct}$

(2) $\varepsilon_{ct} = \eta_c + \mu_{ct}$

And the observed buyout variable is

$$\boldsymbol{Y_{ct}} = \begin{cases} Y_{ct}^{*} & if\ Y_{ct}^{*} > 0; \\ 0 & if\ Y_{ct}^{*} \leq 0\,. \end{cases}$$

Our key explanatory variables include *Fiscal*, representing two variables measuring county *c*'s total property tax revenues and the ratio of property tax revenues to total county government spending. *NFIP* represents a county's flood insurance uptake and average premiums. Note that for all these variables, we use their values one year before the PDD year *t* to address possible simultaneity concerns (i.e., disaster shocks can influence government finance and flood management strategies). *Levee* denotes the percentage of a county's land area protected by levees and other flood control infrastructure.[6] We include the contemporaneous flooding shocks (including flood-related PDDs and rainfall anomalies) and recently experienced flood events in a county, all indicated by *Flood*. *X* represents the vector of other explanatory variables (e.g., a county's socioeconomic, demographic, and political characteristics). Most of these variables are time-varying (except for the variables measuring the percentage of 100-year floodplains and coastal counties) and lagged by one year (*t-1* indicates one year before the PDD) to avoid endogeneity. The year fixed effects, λ_t, control for shocks and changes that are common to all counties within a given year (e.g., changes in national policies that influence buyout programs).

[6] Since a majority of the protective infrastructure was built prior to the starting year of our sample period or with missing built years, we treat this variable as time-invariant.

We also include state dummies, S_c, to control for unobserved heterogeneity across states that influences the implementation of buyout programs. ε_{ct} is the error term.

We estimate a double hurdle model (Cragg 1971) because our buyout data take on properties of a limited dependent variable with a corner solution at zero. The double hurdle model integrates a probit model for estimating the probability of outcome with positive values (e.g., whether or not a county participates in government buyouts) in the first tier and the truncated normal regression for explaining positive values of the outcome (e.g., number of bought-out properties or dollar amount of buyout projects) in the second tier. This approach is considered more flexible than other corner solution models such as Tobit since it allows for the participation and outcome decisions to be determined by separate processes and different factors (Burke, 2009). Estimators in both tiers are obtained by maximum likelihood with standard errors clustered at the county level.

In equation (2), we specify that error term is a function of two components. The first one, η_c, denotes unobserved time-constant county characteristics (or unobserved heterogeneity across counties) that may influence buyout outcomes. These factors may include geographic attributes and a community's culture or collective risk attitude. The second component, μ_{ct}, represents unobserved time-varying shocks that affect local buyout decisions. It should be noted that in nonlinear panel models, the covariates must be independent of unobserved heterogeneity η_c to obtain consistent estimates. In this research, we follow the approach in Ricker-Gilbert et al. (2011) by incorporating a correlated random effects (CRE) framework in the double hurdle model to relax the assumption of independence between μ_{ct} and other covariates (Wooldridge 2002). This is achieved by including a vector of variables measuring the means for all time-varying covariates for each county (except the year dummies). After controlling for the "fixed unobservables", we assume that unobserved time-varying shocks μ_{ct} are random and uncorrelated with the explanatory variables and η_c.

4. Results

Baseline Results

Table 2 reports our estimation results from the double hurdle model of factors that influence county-level government buyout outcomes. Columns 1 and 2 present the two-tier regression results using the total cost of buyout projects as the dependent variable, and columns 3 and 4 are results for explaining the number of bought-out properties. Because our nonlinear model makes it difficult to interpret the estimated coefficients directly, we report our estimates of the average marginal effects in both tiers. Overall, our estimates of the key independent variables are largely consistent for the two buyout measures.

[Table 2 about here]

First, our results indicate that both contemporaneous and recent flooding shocks lead a county to undertake more floodplain buyouts. More specifically, we find that the contemporaneous flood PDD count increases the probability of a county's participation in government buyouts, with its estimated coefficient being statistically significant in the first tier for both buyout outcome variables. But the PDD variable seems to have little effect on either the amount of buyout project costs or the number of bought-out properties in the second tier. This finding is consistent with our expectation since the HMGP funding is triggered by PDDs, even though the grants are not necessarily limited to counties that have received the PDD in that year. The contemporaneous rainfall anomalies, as a measure of flooding magnitude, have a significant, positive effect on buyout outcomes in both tiers. Our estimates suggest that more severe floods not only increase a county's likelihood of engaging in buyouts but also increases buyout participation at the extensive margin. This result further resonates with the previous findings that households who suffer significant property damages from floods are more likely to accept a government buyout offer (e.g., de Vries and Fraser, 2012).

In the meanwhile, we show that recent flooding shocks, measured by the number of PDDs in the past three years, also increase the likelihood that a county engages in floodplain buyouts (as indicated by statistically significant estimates in the first tier), while its effect is less significant in the second tier. This finding suggests that when controlling for contemporaneous shocks, recent flooding experiences still play a role in motivating buyouts. It is noteworthy that while these buyouts reflect policy-driven retreat decisions, our findings also resonate with previous research findings that large-scale disasters induce autonomous relocation and outmigration from risky areas (e.g., Berlemann and Steinhardt, 2017).

Regarding the fiscal factors, we find that a county's total property tax revenues do not influence its likelihood to participate in buyouts (in the first tier) but have a statistically significant and positive effect on the amounts of buyout project costs and bought-out properties, conditional on its participation in buyouts (in the second tier). Our average marginal effect estimates suggest that one percent increase in the total property tax revenues in the previous year is associated with 0.3 percent increase in total costs of buyouts or in the number of bought-out properties in a county. This result supports our hypothesis that counties with a larger tax base tend to undertake more buyouts. We also show that a county's fiscal reliance on property taxes (measured by the ratio of property tax revenues to total spending) is negatively correlated with buyout rates in the second tier, although the variable is statistically insignificant in the first tier. This result, consistent with our expectation, suggests that counties more reliant on property tax revenues undertake fewer property buyouts. As discussed earlier, buyouts-induced relocation may result in a potential loss of tax base and subsequent revenues, which is a more salient issue for counties highly reliant on their own source of revenues from property tax.

We have examined multiple factors to understand the potential influence of a county's existing flood management practice on its buyout outcomes. First, our estimates for the flood insurance take-up rate are statistically significant and negative for both buyout measures in the second tier, which suggests that counties with more flood insurance purchases have fewer floodplain buyouts. Nonetheless, we show that flood insurance take-up does not affect a county's probability of participation in buyouts (in the first tier). These findings are probably not surprising because flood insurance purchase is a household choice and higher flood insurance take-up rates in a county should presumably have a larger influence on buyouts at the extensive margin than on the locality's participation decision (i.e., when the county has more households choosing to buy flood insurance as a means of transferring risks of future losses, it has fewer householder without insurance who may consider the buyout option). Specifically, our estimates suggest that one percent increase in the flood insurance take-up rates in the previous year reduces the total buyout project costs by 0.5 percent and the number of bought-out properties by 0.4 percent, respectively. In the meantime, our estimates for the flood insurance premium variable are positive but statistically insignificant for both buyout outcomes in the two tiers.

With respect to structural projection, our results suggest that a county with more areas protected by flood control infrastructure (e.g., levees) is less likely to participate in floodplain buyouts, as suggested by the negative estimated coefficient (statistically significant at the one percent level) in the first tier. The variable seems to have little effect on the buyout rates at the extensive margin (in the second tier). This result provides empirical support to our hypothesis related to the levee effect. In particular, our finding may suggest that local governments play a role in balancing different hazard mitigation strategies and related policy options (e.g., structural protection versus managed retreat through government buyouts). This finding is consistent with and further expands previous research that suggests public protective structures reduce private agents' incentive to engage in risk mitigation *ex ante* (e.g., Stefanovic, 2003; Boustan et al. 2012).

It should be noted that our empirical analysis also accounts for long-term risk exposure when examining the effects of flooding events and flood management practices. Specifically, we find that the coastal shoreline counties are less likely to participate in buyouts than non-coastal counties, as suggested by the negative estimated coefficient in the first tier. This pattern may resonate with the observed growth of population and development in the U.S. coastal regions (Crowell et al. 2010), and reflect a strong preference for shoreline amenities over flooding risks. The other long-term flood exposure variable, measured as the percentage of a county's 100-year floodplains, is found insignificant to explain buyout outcomes.

As for other control variables, we find that most of the socioeconomic and demographic variables (e.g., personal incomes, poverty rates and unemployment rates) are statistically insignificant. Interestingly, our results show that counties with higher population densities are more likely to undertake buyouts, while larger populations are associated with a lower probability of buyouts and fewer bought-out properties. We also find that the percentage of Democratic voters is positively correlated with the likelihood that a county engages in government buyouts, which may suggest the influence of political ideology.

In addition to the baseline analysis above, we undertake a robustness check by estimating a panel count-data model for our dependent variable measuring the number of bought-out properties. Our estimation results, reported in the online appendix, are consistent with our baseline findings on our key variables of interest.

Extension

As discussed earlier, HMGP funds a variety of projects that aim at reducing long-term flood risks, with government buyouts being the largest spending category. Government-sponsored retreat including buyouts mitigates risks by reducing human exposure, and it is different from other projects that focus on enhancing local hazard mitigation capacities, such as flood control infrastructure, structural elevation and retrofit, and warning systems. These mitigation projects may have the potential to attract more in-migration as opposed to out-migration from risky regions. Considering these distinctions, we undertake an extension to examine whether the factors that influence a county's buyout outcomes also influence its choice of other mitigation projects in the same way. For instance, do higher flood insurance take-ups discourage local investment in other hazard mitigation strategies? Specifically, we create a variable measuring the cost of all other projects funded through HMGP (excluding buyouts) following a flood or storm PDD, and regress this variable on the same set of explanatory variables that are included in our model for buyouts. Table 3 reports the estimation results using the baseline double hurdle model.

[Table 3 about here]

Our results show that both the contemporaneous and recent flood PDDs increase a county's likelihood to invest in non-buyout-related hazard mitigation with HMGP funding. The contemporaneous PDDs are also found to increase these project spending in the second tier. Interestingly, we find that the rainfall anomaly has a negative estimated coefficient in the first tier, but its effect turns positive in the second tier. One possible explanation is that counties that experience severe floods may more likely receive grants from Public Assistance (PA), which is

FEMA's major grant program providing post-disaster assistance to state and local governments, to cover their local mitigation project costs. In contrast with our findings on buyouts, we finding that neither the fiscal variables nor the flood insurance take-up rates is statistically significant in two tiers, which may suggest their limited influences on local decisions related to enhancing mitigation capacities. With respect to the long-term flood exposure, we find that counties with more areas located in the 100-year floodplains are more likely to undertake non-buyout-related hazard mitigation projects. Our results also show that coastal shoreline counties, on average, invest more in non-buyout-related mitigation projects supported by HMGP grants than non-coastal counties. This result, in stark contrast with our finding on buyouts, may suggest a strong preference of coastal communities for strategies enhancing mitigation capacities (e.g., structural protection) over reducing exposure and managed retreat. We also find that counties with more democratic voters tend to have fewer HMGP-funded mitigation projects excluding buyouts. Overall, our results shed light on the differential influences of disaster insurance, community characteristics, and geography on local choices of buyouts vs. other hazard mitigation projects.

5. Conclusion and Discussion

As climate change unfolds, extreme weather events including floods, hurricanes, and severe storms are expected to increase in both frequency and intensity. Retreat and relocation from high-risk areas is an essential strategy for mitigating flood losses and adapting to climate change. Given the significant discretion of local governments in land-use decisions, it is critical to understand how local fiscal institutions, policy context, and community characteristics jointly influence participation decisions in government buyouts.

In this paper, we use a national sample of HMGP-funded buyout projects to empirically examine the factors influencing floodplain buyouts at the county level. We find that counties with more property tax revenues or a lower fiscal reliance on property taxes undertake more floodplain buyouts. This finding suggests that local fiscal resources and costs of buyouts are critical factors that shape local government decisions related to property buyouts. While there is little empirical evidence confirming the negative impact of buyouts on local tax revenues, this problem can be potentially alleviated by policies that encourage buyout participants to relocate within the same county. It is equally important for local governments to quantify buyouts-related benefits (e.g., future flooding losses avoidance, environmental amenities of open areas) and the fiscal costs of buyouts (e.g., possible tax revenue loss, the maintenance cost of buyout sites) to better assess the feasibility of buyout programs.

We also find that higher flood insurance take-up rates are associated with smaller amounts of floodplain buyouts. Important for policy considerations, our findings suggest that the subsidized flood insurance may serve as an obstacle to managed retreat and raise the question about the welfare implications of NFIP. To address the perverse incentive problem caused by flood insurance may require continued reforms of NFIP that gradually eliminate most flood insurance subsidies and bring premiums to the full-risk rates.[7]

Our results further suggest the potential crowd-out effect of the existing flood control infrastructure, as we find that counties with more levee protection undertake fewer buyouts. This finding particularly warrants attention in the context of structural soundness and maintenance need for federally-funded infrastructure in the U.S. The recent dam failure in Michigan has exposed this critical gap and potential threats to the built environment. Our research also provides suggestive evidence that coastal counties are less likely to engage in buyouts but rather

[7] While previous NFIP reforms including the 2012 Biggert-Waters Flood Insurance Reform Act had attempted to phase out key NFIP subsidies, the progress of subsidy removal has been partially tempered by the 2014 Homeowner Flood Insurance Affordability Act (GAO 2015).

rely more on other strategies for improving local hazard mitigation capacities. Overall, our research findings provide important policy implications for flood risk management and climate change adaptation. Given the wide range of options for managing flood risks (e.g., structural and non-structural protection, provision of flood insurance and mitigation incentives), it is crucial for policymakers to understand the interplay and long-term compatibility of these different approaches for making rational choices.

Finally, we acknowledge the limitations of this study. First, it should be noted that flood insurance uptake, as a choice variable, is potentially endogenous as it may correlate with unobserved time-varying county characteristics that affect buyout decisions. Although our approach controls for the time-constant unobserved heterogeneity, it does not fully address the omitted variable problem. Second, this study focuses on the effect of fiscal resources on local buyout decisions and does not directly examine the fiscal impacts of government buyouts, which involves not only their direct effect on tax bases and revenues but also long-term impact on housing values and community resilience. Considering the critical role of local governments in land use and development decisions, more attention and research should be devoted to the dynamic linkage between local government finance and disaster risk management (e.g., how fiscal conditions influence local policies for risk mitigation, and how different mitigation strategies, in turn, affect public finance such as budgets, tax revenues, and government spending).

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Table 1. Summary Statistics

	Mean	**Std. Dev.**	**Min**	**Max**
Dependent variables				
Total buyout projects costs (log)	1.4638	4.2097	0	19.0659
Number of bought-out properties (log)	0.20043	0.7201	0	6.9594
Independent variables				
Flood-related PDDs	0.9701	0.6312	1	5
Rainfall Anomalies	0.5438	1.0403	-4.3023	5.5816
Flood-related PDDs in past three years	0.9589	1.0788	0	7
Insurance take-up rate (log of policies-in-force per 1,000 people)	1.6755	1.11367	0	6.4964
Premium per $1,000 coverage (log)	1.6459	0.4510	0	3.9396
Levee protected area (%)*	2,4922	10.7049	0	100
Total property tax revenues (log)	8.8728	1.5406	0	15.3941
Property tax-spending ratio (%)	28.53356	18.01048	0	513.8527
Personal incomes per capita (log)	10.2693	.2843	9.2518	11.8846
Poverty rate (%)	14.5347	5.6053	2.5	46.8
Unemployment rate (%)	6.0804	2.53560	.8	29.9
Housing price index	222.3614	134.6951	72.94	1399.69
Net inflows/population	0.0015	0.0095	-0.0823	0.1480
Population (in thousand persons)	110. 963	382.243	0.055	10137.92
Population density (thousand persons/square kms)	0.0803	.4918	0.0000148	18.641
People at least 65 years old (%)	15.1672	3.8265	4.1918	54.8283
Black populations (%)	9.5486	13.9231	0	85.4557
Voting for a Democratic candidate (%)	41.2376	11.1968	7.9005	88.8697
Coastal county (=1)*	0.0940	0.2919	0	1
Flood zone ratio (%)*	12.2073	13.8585	0	100

Notes: The regression sample contains a total of 2,510 counties and 12,855 county-year observations. * indicates the variable is time-invariant.

Table 2. Results for modeling county-level buyouts of floodplain properties using double hurdle model

Dependent variables	(1) Tier 1 ***Buyout project costs***	(2) Tier 2	(3) Tier 1 ***# of bought out properties***	(4) Tier 2
Flood-related PDDs (t)	0.0542***	0.105	0.0492***	0.121
	(0.00463)	(0.0745)	(0.00442)	(0.0749)
Rainfall Anomalies (t)	0.0172***	0.135***	0.0171***	0.219***
	(0.00278)	(0.0419)	(0.00271)	(0.0452)
Past flood PDDs	0.00818**	0.0495	0.00695*	0.0807*
	(0.00274)	(0.0509)	(0.00271)	(0.0456)
Total property tax revenues	-0.000655	0.311***	0.00418	0.349**
	(0.0115)	(0.110)	(0.0115)	(0.152)
Property tax-spending ratio	-0.000373	-0.00838**	-0.000365	-0.0107**
	(0.000416)	(0.00422)	(0.000376)	(0.00514)
Flood insurance take-up rates	-0.0105	-0.556**	-0.00535	-0.423*
	(0.0128)	(0.238)	(0.0121)	(0.235)
Average insurance premium	0.0106	0.551	0.0147	0.348
	(0.0115)	(0.344)	(0.0108)	(0.322)
Coastal county	-0.0598***	-0.363*	-0.0551***	-0.285
	(0.0105)	(0.213)	(0.00952)	(0.193)
Levee protection	-0.00151**	-0.00292	-0.00133**	-0.00637
	(0.000491)	(0.00569)	(0.000419)	(0.00558)
Flood zone ratio	-0.00369	-0.655	-0.0130	-0.538
	(0.0280)	(0.443)	(0.0259)	(0.374)
Personal incomes per capita	0.0377	-0.216	0.0214	-0.194
	(0.0390)	(0.611)	(0.0371)	(0.642)
Poverty rate	0.00329	0.00629	0.00176	0.00197
	(0.00203)	(0.0327)	(0.00193)	(0.0311)
Unemployment rate	0.00205	0.0220	0.00235	0.0286
	(0.00246)	(0.0369)	(0.00242)	(0.0394)
Housing price index	-0.000116	0.00136	-0.0000855	0.00111
	(0.0000662)	(0.000988)	(0.0000616)	(0.00106)
Net inflows of population	0.0456	3.411	-0.0427	7.205
	(0.403)	(10.19)	(0.396)	(8.551)
Population	-0.000186*	-0.00187	-0.000206*	-0.00347**
	(0.0000948)	(0.00150)	(0.0000952)	(0.00175)
Population density	0.528*	2.150	0.585*	5.241
	(0.260)	(5.236)	(0.244)	(5.940)
% Elderly	0.00479	0.00971	0.00297	0.0993
	(0.00417)	(0.0642)	(0.00369)	(0.0611)
% Black populations	0.00383	-0.0480	0.00345	-0.0207
	(0.00318)	(0.0305)	(0.00297)	(0.0297)
% Voting for a Democratic candidate	0.00207**	-0.00788	0.00120*	-0.00637
	(0.000723)	(0.0105)	(0.000675)	(0.0106)
Observations	12,855		12,855	
Number of counties	2,510		2,510	

Notes: All time-varying variables except for flood PDDs and rainfall anomalies are lagged by one year. All the specifications include year fixed effects, state dummies, and time average of all time-varying explanatory variables (except the year dummies). The estimated coefficients report the average marginal effects obtained by margins command in Stata, and the standard errors of average marginal effects are calculated using the delta method.
p<0.1; ** *p*<0.05; *** *p*<0.01.

Table 3. Results for modeling other mitigation project costs at the county level

	Tier 1	Tier 2
Flood-related PDDs (t)	0.154***	0.329***
	(0.00779)	(0.0455)
Rainfall Anomalies (t)	-0.0306***	0.0580**
	(0.00436)	(0.0289)
Past flood PDDs	0.0230***	0.0230
	(0.00419)	(0.0294)
Total property tax revenues	-0.00909	-0.0953
	(0.0148)	(0.105)
Property tax-spending ratio	0.000561	-0.00105
	(0.000389)	(0.00199)
Flood insurance take-up rates	0.00548	-0.0422
	(0.0192)	(0.123)
Average insurance premium	0.000522	0.0345
	(0.0161)	(0.122)
Coastal county	0.0288	0.300***
	(0.0202)	(0.115)
Levee protection	-0.000439	0.000826
	(0.000419)	(0.00266)
Flood zone ratio	0.0902*	0.363
	(0.0383)	(0.224)
Personal incomes per capita	0.00668	-0.201
	(0.0509)	(0.311)
Poverty rate	0.00314	0.00173
	(0.00290)	(0.0177)
Unemployment rate	0.00163	0.0584**
	(0.00400)	(0.0260)
Housing price index	-0.000288**	-0.000491
	(0.0000988)	(0.000589)
Net inflows of population	-0.380	-1.635
	(0.626)	(3.931)
Population	0.000416	-0.00245*
	(0.000245)	(0.00130)
Population density	0.360	5.027*
	(0.533)	(2.836)
% Elderly	0.00369	0.0209
	(0.00521)	(0.0320)
% Black populations	-0.00000461	0.00291
	(0.00499)	(0.0240)
% Voting for a Democratic candidate	-0.00417***	-0.0129**
	(0.00111)	(0,00596)
Observations	12,855	
Number of counties	2,510	

Notes: All time-varying variables except for flood PDDs and rainfall anomalies are lagged by one year. Both two tiers include year fixed effects, state dummies, and time average of all time-varying explanatory variables (except the year dummies). The estimated coefficients report the average marginal effects obtained by margins command in Stata, and their standard errors are calculated using the delta method.
* p<0.1; ** p<0.05; *** p<0.01.

Appendix for "Managed Retreat in the Face of Climate Change: What Influences Buyouts of Flood-prone Properties"

As a robustness check, we exploit the count-data nature of our dependent variable measuring the number of bought-out properties and estimate a Poisson fixed effects model with robust standard errors (Cameron & Trivedi, 2005).[8] We included the county fixed effects to control for the time-invariant unobserved heterogeneity across counties and year dummies to control for common national shocks in a given year. Table A1 reports our estimation results.

We find that the flood-related PDDs and rainfall anomaly variables all have a positive and statistically significant effect on buyouts, a pattern that is similar to our baseline findings. Regarding the fiscal variables, our results show that a county's total property tax revenue has a positive correlation with its bought-out properties, while the tax ratio variable, which measures fiscal reliance on property taxes, has a negative estimated coefficient (statistically significant at the 1% level). Our estimates that one percent increase in total property tax revenues in the previous year is associated with 0.24 percent increase in the number of bought-out properties, and one percent increase in the ratio of property tax revenues in spending decreases buyouts by 0.025 percent. The flood insurance take-up rates are also found to negatively correlate with the number of bought-out properties, which is consistent with our findings in the baseline model. In addition, our results show that counties with higher personal incomes per capita have fewer buyouts, as suggested by the negative estimated coefficient on this variable. This finding seems

[8] This model is preferred to the fixed effects negative binomial model as the latter does not truly control for unobserved fixed effects (Cameron & Trivedi, 2005; Wooldridge, 2002). The robust standard errors in the Poisson fixed effects model can address the over-dispersion in the data. The Poisson model allows us to interpret the estimated coefficients using either semi-elasticity for variables in levels or elasticity for variables in logs.

Table A1. Results for modeling county-level bought-out properties

Flood-related PDDs (t)	0.396***
	(0.110)
Rainfall Anomalies (t)	0.496***
	(0.0751)
Recent flood PDDs	0.297***
	(0.0662)
Total property tax revenues	0.237*
	(0.123)
Property tax-spending ratio	-0.0249***
	(0.00944)
Flood insurance take-up	-0.663**
	(0.322)
Average insurance premium	0.665
	(0.492)
Personal incomes per capita	-2.958**
	(1.232)
Poverty rate	0.00778
	(0.0532)
Unemployment rate	0.0466
	(0.0614)
Housing price index	-0.000443
	(0.00136)
Net inflows of population	10.49
	(9.877)
Population	-1.374
	(1.465)
Population density	9.018
	(67.93)
% Elderly	0.00227
	(0.0884)
% Black populations	-0.0207
	(0.0529)
% Voting for a Democratic candidate	0.00502
	(0.0169)
Observations	12,855
Number of counties	2,510

to resonate with Mach et al (2019) in suggesting that communities with lower incomes tend to undertake more buyouts.

Notes: In parenthesis are standard errors clustered by county. All variables except for flood PDDs and rainfall

anomalies are lagged by one year. The model includes county and year fixed effects. The time-constant variables including levee protection, coastal county, and flood zone ratio are subsumed by the county fixed effects.
* $p<0.1$; ** $p<0.05$; *** $p<0.01$.

Figures

Figure A1: Spatial distribution of total number of buyout properties by county (PDD years 1990-2016)

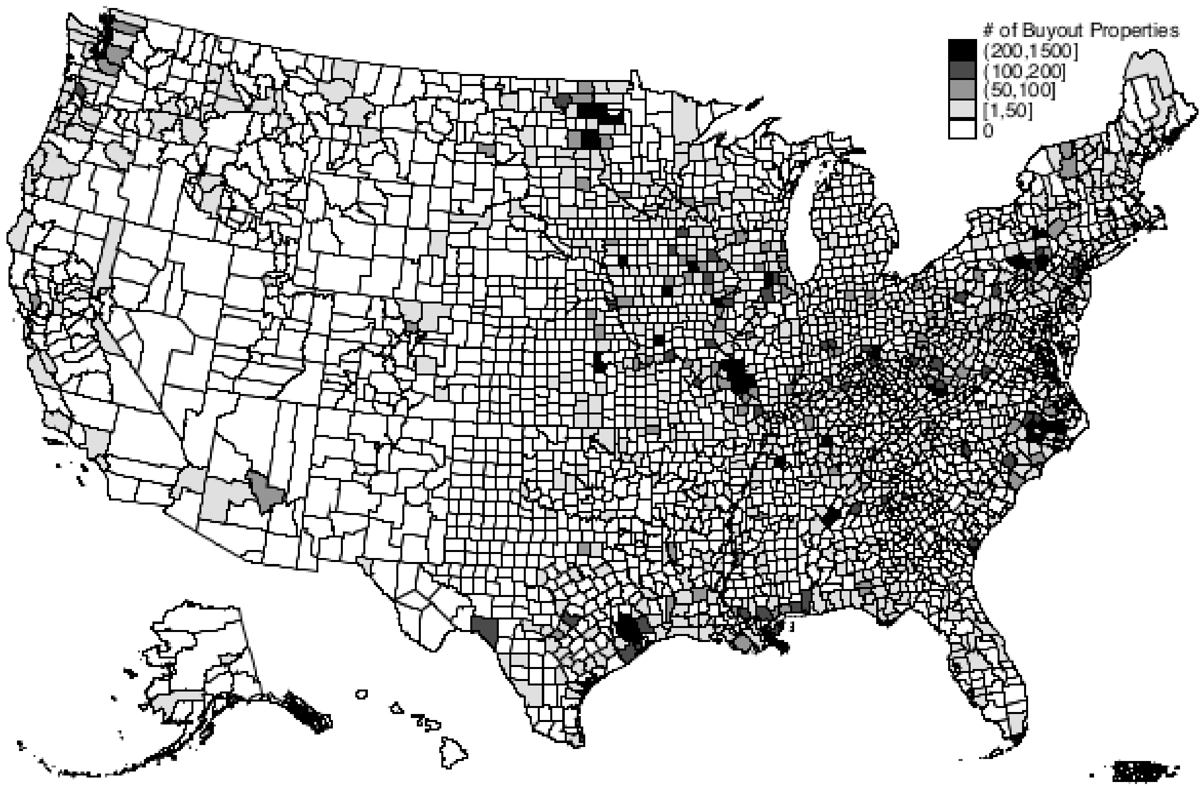


Figure A2: Cumulative Costs of Buyout Projects by County (PDD years 1990-2016)

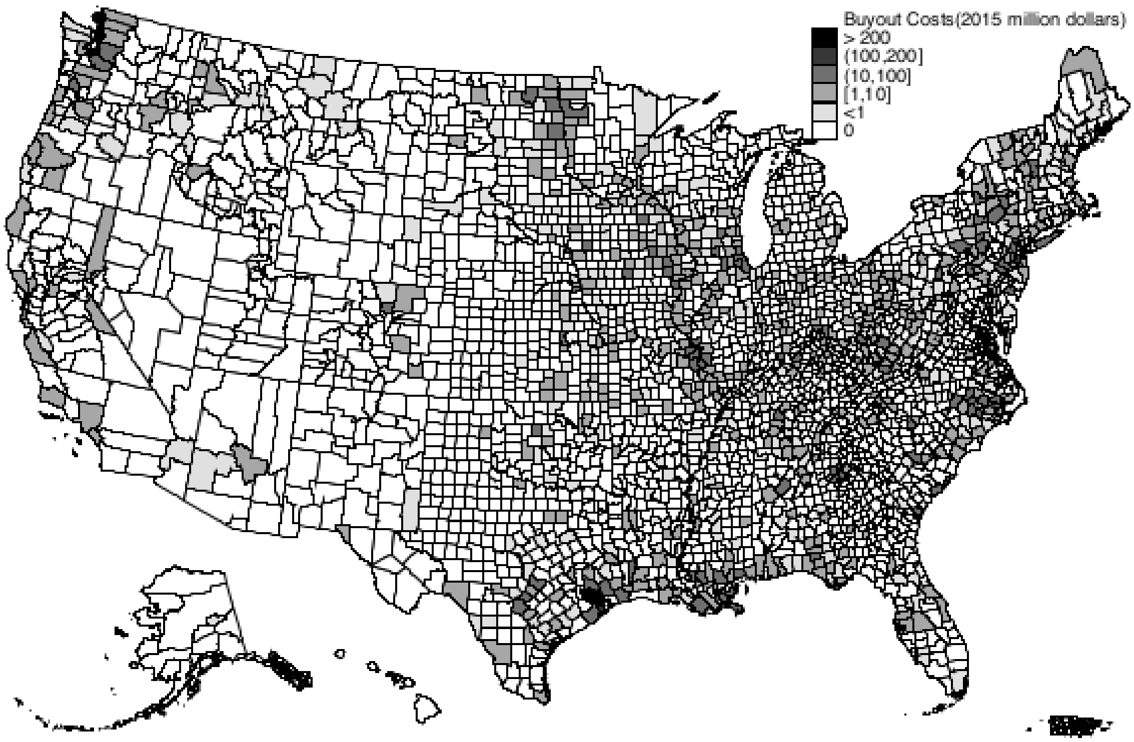
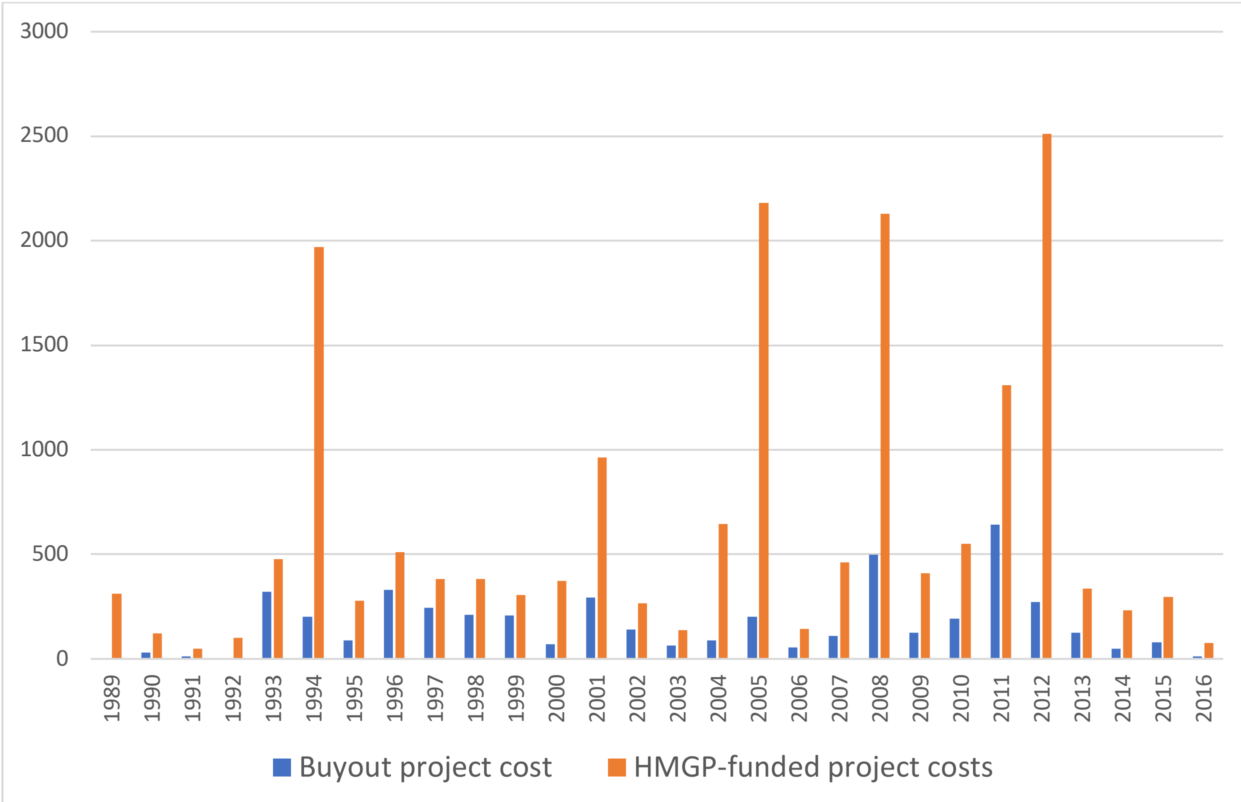


Figure A3. Annual HMGP-funded Project Costs and Buyout Project Costs (in million 2015 dollar) by PDD year



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