Barriers to Coastal Managed Retreat: Evidence from New Jersey's Blue Acres Program

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ABSTRACT

Managed retreat is a climate adaptation strategy involving government buyouts of at-risk properties that is currently underutilized in coastal areas of the United States. These programs often require both voluntary homeowner applications and municipal government support for a successful buyout. We use a conceptual framework and a set of empirical models with data from a buyout program in a coastal state to develop descriptive evidence on potential barriers to successful managed retreat policies in high-risk coastal areas. Key factors influencing buyout success can be associated with municipal budgets, including revenues, expenditures, debt, and government transfers. Importantly, revenue impacts related to property taxes appear to contribute to fewer buyouts, suggesting a potential principal-agent problem related to climate resilience in high-value coastal housing markets. Recognition of the combination of factors that may represent barriers to adoption may help the design and implementation of future programs and improve coastal climate adaptation strategies.

Keywords: buyout programs, climate change adaptation, managed retreat, principal-agent problem, sea-level rise

JEL codes: H72, Q54, Q56, Q58

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1. INTRODUCTION

As the effects of climate change begin to materialize in developed coastal areas through increased storm activity and sea-level rise (SLR), recent evidence suggests a need for significant public and private action in coastal adaptation to avoid damages to trillions in capital assets (Hinkel et al., 2014) and displacement of millions of people (Hauer et al., 2016). Changing land use or land-use policies provide local governments adaptation pathways with three general policy options: protect, restore, or retreat (Fankhauser 1995; Kousky 2014). Protection with engineered structures, such as shoreline armoring or sea walls, is predicted to be a significant share (> 59 percent) of future coastal adaptation expenditures (Neumann et al. 2015). Restoration of natural ecosystems as a barrier to coastal hazards can mitigate some risks (Arkema et al. 2013). Billions have been spent on beach nourishment to replenish sand on nearly 900 miles of the United States (U.S.) coastline (NOAA 2020), although the cost-effectiveness of this strategy is debated (Dundas 2017). Coastal wetlands produce nearly \$1.8 million/km^2 in annual protection services (Sun and Carson 2020), and losing these wetlands can be costly to society (Taylor and Druckenmiller 2022).

The third option, and the focus of this paper, is managed retreat. This strategy is a government-funded response to help mitigate hazard risk and involves the intentional movement of homes and infrastructure away from the source of the risk. It is often viewed as an option of last resort when protection and restoration are not economically or ecologically feasible. This is largely the case despite advantages of retreat in providing new open space to act as a physical buffer to SLR and coastal erosion, eliminating recurring rebuilding costs, and providing synergies with restoration (i.e., providing space for dunes or wetlands to migrate). Voluntary buyouts of residential homes are the primary mechanism of current retreat policy in the U.S. (Hino et al. 2017; Mach et al. 2019; Elliott et al. 2020). Retreat has generally been reactive, with new activity coinciding with extreme weather events (e.g., large hurricanes like Sandy, Michael, and Henry), but the scale of implementation is relatively small compared to resources devoted to *ex-post* disaster aid. The U.S. Federal Emergency Management Agency (FEMA) has funded \$89 billion in disaster-related public assistance through grants to state governments since 1998, with only 4.5 percent (\$4 billion) allocated to private property buyouts. There is recent anecdotal evidence that some municipalities are restricting new housing developments in flood-prone areas (Flavelle and Schwartz 2019), but common U.S. post-disaster practice is for local jurisdictions to apply for federal funding to rebuild rather than to relocate.

To date, there is wide spatial variation in uptake in voluntary buyouts, but existing programs have generally had more success with buyouts in inland floodplains than in high-risk coastal areas (Fig. 1, panel A). The historical trend of property acquisition by FEMA shows that buyouts peaked in 1993 and have slowly declined since then despite an increase in costly natural disasters (Fig. 1, panel B). At the local government scale, there are a number of unknowns about the decision to engage and participate in retreat policies that include buyouts of private property (Siders 2019). For one, local governments may be hesitant to send a risk signal to housing markets.[1] Furthermore, the current complex coastal disaster policy landscape focuses on *ex-post* response to damaging events, despite mounting evidence that *ex-ante* investments may be more effective (e.g., Davlasheridze et al. 2017). Low-probability, high-consequence events such as floods are likely to trigger government action as a response to public sentiment, often leading to inefficient or even maladaptive long-run responses (Anderson et al. 2018). Federal and state policies may also influence municipal and private landowner behavior (e.g., FEMA's Individuals and Households Program (IHP) and Hazard Mitigation Grant Program (HMGP)), which may, in turn, alter incentives to participate in buyout programs (e.g., Kousky et al. 2018).

Our primary focus here is to examine a state-level voluntary buyout program and develop descriptive empirical evidence that points to important obstacles to uptake of managed retreat policies in high-risk coastal areas. We explore this question using data on nearly 700 property buyouts over six years (2013 - 2018) in the U.S. state of New Jersey (NJ) after Hurricane Sandy. Data from the New Jersey Blue Acres Program (NJBAP) allows us to observe the location of successful buyouts and number of applications received by the state from each community. Importantly, a successful buyout in NJBAP requires both a voluntary application from a homeowner and support for the program at the municipal level. For example, a municipality may have 35 applications for the buyout program, but none will be successful without direct programmatic support from the local government. A cursory examination of successful buyout

[1] As an example in California, Del Mar's walkable beach is expected to disappear and many affluent neighborhoods will be inundated by 2050. Yet, homeowners are concerned a formalized plan to retreat would harm property values (Rott 2018). In Pacifica, residents are worried that the city will become "an economic wasteland" if the long-term vision is retreat (Xia 2019).

locations illustrates the context of our research question. For the four coastal counties in NJ, the areas most affected by Hurricane Sandy, only seven (7) buyouts (1 percent of total) were successful. Interestingly, all seven were located along one street with creek flooding in an inland township (i.e., no ocean or coastal bay shoreline). There were no successful buyouts in coastal municipalities in these four high-risk counties. Of the 24 municipalities deemed at highest risk under NJBAP criteria (i.e., most likely to benefit from the program), 20 (83 percent) are in these four coastal counties, yet none had a successful buyout. Importantly, these same areas saw significant homeowner applications to the program. Nearly 50 percent of all applications to NJBAP came from these four counties, and 95 percent of those applications were from municipalities with ocean or coastal bay shorelines. Of these 81 coastal towns, 43 (53 percent) had residents offer voluntary buyout applications to the program, but no successful buyouts occurred. These observations reinforce our question: what are the barriers preventing voluntary buyouts in coastal areas with high-hazard risk?

Our primary contribution to the literature is analyzing local government decision-making with respect to a managed retreat program with the goal of understanding the barriers to adoption in coastal settings. We first describe a conceptual framework for how a municipal government may make decisions about support for a voluntary buyout program based on the program's impacts on local budgets through revenues, expenditures, debt, and government transfers. We then present two modeling approaches to address our question empirically, a single-stage count data model regressing the number of successful buyout counts on municipal budget variables and a two-stage decision model that reflects the need for both voluntary homeowner applications and local government support for successful buyouts to occur. A few key consistencies emerge across our specifications. First, revenue effects related to property taxes may be a significant barrier to buyout programs. Both buyout counts and municipal support of applications decline as the average tax assessment value of residential properties increases, and the share of property taxes in total municipal revenue rises. This suggests revenue effects from a reduction in a municipality's tax base may drive decisions on hazard planning rather than goals to make the community more resilient to those hazards (i.e., a potential principal-agent problem). Municipal debt may also play a role in the support decision, as towns with higher long-term debt as a percentage of total revenue are more likely to support applications, suggesting recently announced changes in how credit rating agencies view climate risk (e.g., Moody's 2017) may be encouraging support of managed retreat policies in high-risk areas. We also show that as the share of municipal expenditures on public goods rise, municipal participation in a buyout program is likely to decline. Our results also suggest municipal governments are likely to focus on short-term or current hazard risks, with buyout counts being higher in areas with higher shares of properties in FEMA flood zones but lower in areas vulnerable to future SLR inundation. We find mixed evidence on the effect of government transfers on buyout counts and municipal support. In the single-stage model, *ex-post* aid does not impact buyout counts, and higher *ex-ante* resilience investment is correlated with lower buyout counts. In the two-stage Heckman model, municipalities with more *ex-post* aid are less likely to support buyouts, and those with *ex-ante* investments are more likely to support buyouts.

Our analysis provides a conceptual framework and descriptive empirical evidence about potential institutional barriers to successful implementation of managed retreat policies. Given the importance of local government involvement in the retreat process, our analysis fills a critical gap in guidance to policymakers on development and implementation of managed retreat as a climate adaptation strategy (Woodruff and Stults 2016). This land-use option is likely to become a crucial adaptation tool in many coastal areas (Kousky 2014) as it provides an alternative to investments in protection of existing assets or restoration of natural defenses.

2. POLICY SETTING

In prior empirical studies of coastal climate adaptation, the primary focus has centered on housing market responses to risks and investments to mitigate those risks. Discounts from flooding events may capitalize into housing values, but these effects may not be persistent (Atreya et al., 2013; Bin and Landry, 2013). Early work on the economic impacts of SLR to property markets suggests large potential damages (Yohe et al. 1995, 1996) with estimates for the U.S. reaching $2 billion (1990 USD) (Yohe and Schlesinger 1998). Bin et al. (2011) estimate property market losses in North Carolina alone at over half a billion dollars by 2080 due to SLR. Recent evidence on the effect of future SLR is mixed, with heterogeneous risk beliefs across coastal homeowners (Bakkensen and Barrage 2022) and impacts that vary across market segments (Bernstein et al. 2019). Erosion is also a concern and may generate damages of $150 to $320 million (2000 USD) by 2050 in

Delaware (Parsons and Powell 2001; Wakefield and Parsons 2003). Investments in coastal adaptation have been shown to capitalize significantly and relatively consistently into coastal housing markets. Such expenditures can be made by governments to provide protection for housing through beach nourishment and sand dune construction (Dundas 2017; Qiu and Gopalakrishnan 2018) or privately by individuals through bulkheads, seawalls, or rip-rap revetments (Dundas and Lewis 2020; Walsh et al. 2019). Investments in maintaining or restoring coastal ecosystems also hold significant potential for increasing coastal protection and other important ecosystem services (Arkema et al. 2013; Sun and Carson 2020; Taylor and Druckenmiller 2022).

With managed retreat, economic analyses are limited.[2] Kousky (2014) provides important policy guidance on the use of managed retreat to restrict risky development and move vulnerable housing and infrastructure away from hazard areas. Landry et al. (2020) estimate that both beach users and non-users would be willing to pay $22 per household per year for shoreline retreat policy in North Carolina, and Ando and Reeser (2022) estimate homeowner willingness to pay for a pre-flood buyout contract in a national study in the U.S. Recently, Hashida and Dundas (2023) show heterogeneous housing market impacts across space and buyout types associated with a state-level buyout program in the state of New York. Work from other disciplines has focused on households' decisions to rebuild or relocate (Binder et al. 2015) and development of a conceptual model of managed retreat (Hino et al. 2017). Siders (2019) suggests U.S. buyout programs lack transparency and involve a series of subjective decisions that could allow officials to purposefully target communities for retreat to either maliciously remove particular segments of the community, pragmatically target affordable housing to stretch limited budgets, or beneficially aid those at greatest risk. Two recent national-level analyses of FEMA's buyout program focus on determining variables common across counties with buyouts (Mach et al. 2019) and racial inequality in FEMA program implementation (Elliott et al. 2020).

Our empirical setting is New Jersey, a U.S. coastal state with 130 miles of shoreline on the Atlantic Ocean. The NJBAP was the first and remains one of the few standing state-level programs to acquire flood-prone properties in the U.S. The program offers eligible homeowners of at-risk

[2] A search on December 28th, 2022 on EconLit using the term "managed retreat" yields only 11 results, with one (1) of the 11 published in economics journals (Clément et al. 2015).

properties buyouts at a pre-disaster market value of their homes. NJBAP began in 1995, although major funding for the effort was limited until after Superstorm Sandy (October 2012). Due to funding commitments from FEMA and the NJ state government post-Sandy in early 2013, buyout activity expanded sharply. NJ voters approved additional funding for the program in 2014 through a new corporate business tax. The program is administered by the New Jersey Department of Environmental Protection (NJDEP) and is funded primarily by FEMA's HMGP and the Department of Housing and Urban Development (HUD) Community Development Block Grants Disaster Recovery Program. The NJBAP website contains resources about the basics of the program, homeowner eligibility, steps of the buyout process, guidance on finding a real estate attorney, and answers to frequently asked questions. NJBAP applications are available in both English and Spanish and can be submitted online or via the postal service. NJBAP follows a FEMA guideline that requires a benefit-cost analysis for a property if acquisition costs exceed $276,000 and federal funds are utilized.[3]

For homeowners to be eligible for the program, they must have experienced flood damage from Sandy or repeated flood damage from previous events and have a member of the household be a U.S. citizen, non-citizen national, or qualified alien (if federal funds are used). Maintaining a flood insurance policy with National Flood Insurance Program (NFIP) is also required if funds from FEMA's Flood Mitigation Assistance program are used. The process for a buyout begins with voluntary applications from eligible individual homeowners. For this homeowner application to be considered by NJBAP, the homeowner's municipality must support applications in their town and partner with the state through the buyout process. Supporting municipalities are expected to assist residents with the buyout process and help NJBAP with project coordination. When a

[3] Many homes in NJ fall above this threshold, with the average home in NJ valued at $461,990 in June 2022 according to the Zillow Home Value Index. The pre-Sandy median sales price (September 2012) was $268,000. In our analysis, we do not observe sales prices nor do we observe buyout payment amounts. We do observe the averaged assessed value of property in each municipality (see Figure S2 panel A in the online appendix). In municipalities with buyouts, the average assessed value is below the $276,000 threshold and in municipalities without buyouts, assessed value is higher than the threshold. A concern here is that this FEMA requirement for a benefit-cost analysis could be driving the decrease in buyout for higher valued homes. To test this, we added an indicator variable for municipalities with assessed values below the threshold and we find no significant differences in any model we present in this manuscript with or without the indicator. The FEMA threshold for a benefit-cost analysis was recently increased to $323,000 per structure (https://www.fema.gov/sites/default/files/documents/fema_acquisition-elevation-precalculated-benefits-memo_092021.pdf).

voluntary application from a supporting municipality reaches the NJBAP, the NJDEP then selects parcels to buyout given program budget constraints and with preferences given to clusters of flood-prone homes with histories of NFIP claims, investments that are deemed cost-effective, and those that provide an "opportunity for significant environmental impact and/or improvement to public health, safety, and welfare" (NJDEP Blue Acres FAQ).[4] Applicants from selected parcels receive a pre-Sandy market value payment for their home, and then the state and municipality coordinate on demolishing the structure. After demolition, the land is permanently preserved as open space to aid in flood control and may be accessible to the public for recreation. As our schematic diagram shows (Figure 2), a successful buyout requires both a voluntary application from an eligible homeowner and municipal government support for buyouts, and then selection of the parcel by the state program. Our focus in this paper is the role of municipal government, and this policy landscape directly informs our conceptual framework (Section 3) and empirical models (Section 5) to investigate uptake of government-led managed retreat efforts.

New Jersey and the NJBAP make a compelling study area for our analysis for several reasons. First, NJ has a historically high dependence on federal disaster aid. Homeowners in NJ have received \$500 million (~ \$5,000 per applicant) from FEMA's IHP since 2004, which places the state as the sixth-largest recipient in the country (OpenFEMA Dataset: Housing Assistance Data. 2020). The state is also the sixth-largest recipient of HMGP funds, and more importantly, it has one of the highest federal cost-share percentage at 78 percent - only Northern Mariana Island, Mississippi, and Guam exceed this level.[5] New Jersey is the fifth largest NFIP policyholder, with 222,000 insured units and \$56 billion in insurance coverage, according to FEMA NFIP claims data. The state has also secured \$1.43 billion in federal expenditures for beach nourishment to protect coastal real estate (NOAA 2020). Second, at the time, Hurricane Sandy was the second-largest Atlantic hurricane in U.S. history and the second costliest, resulting in roughly \$50 billion in damage to coastal areas across the Eastern Seaboard (Blake et al. 2013). During Sandy, high

[4] The buyout selection criteria are listed on NJBAP website, https://dep.nj.gov/blueacres/faq/, under the tab "How does DEP decide where to conduct buyouts? What are the criteria?" The NJDEP does not further define "welfare" and leaves this open for interpretation.
[5] Federal cost share during the period of this study was dependent on the type and nature of disaster aid (https://www.fema.gov/hmgp-appeal-categories/cost-sharing) and specific relationships between federal and state agencies. For example, a typical federal cost share is 75 percent but a state's governor can make specific requests for FEMA to cover a larger percentage. H.R. 247 (Consolidated Appropriations Act) was signed in March 2022 and increased federal cost share to 90 percent in the event of a major disaster declaration.

water levels were recorded up to 9 feet above normal in some coastal counties in New Jersey (Ingargiola et al. 2013). The NJBAP offered an alternative policy response to common post-disaster funding from FEMA and NFIP.

Lastly, there is a notable lack of buyouts in coastal areas where eligibility for NJBAP is high. Figure 3 panel A shows the spatial distribution and the density of buyout applications at the municipality level. In our sample of 564 municipalities, 133 (23.6 percent) had at least one homeowner application to NJBAP, but only 14 of the 133 municipalities with applications had successful buyouts. There were 54 municipalities with multiple applications that did not participate in the program. Of the 31 municipalities that had greater than 10 applications, only 12 participated, and none were towns with ocean or bay shorelines. Figure 3 panel B highlights this disconnect between the high-risk coastal areas with applications and the inland areas that received buyouts.

What differentiates municipalities that actively supported the buyout process from those that choose to partner with NJBAP? Consider a comparison of two municipalities: Woodbridge Township and Toms River. These communities are similar in size, with about 25,000 and 35,000 residential parcels, respectively. However, Toms River residents appear to be at significantly higher risk of damages from flooding than residents of Woodbridge. For instance, almost a third of residential properties in Toms River are in a flood zone and nearly 3,500 households received FEMA IHP aid after Sandy. Less than two (2) percent of residential parcels in Woodbridge are in a flood zone and only 304 households received post-Sandy IHP aid. Despite the evidence of a higher level of risk in Toms River, the town had zero buyouts because the municipal government refused to support any of the 32 applicants to NJBAP. Woodbridge, on the other hand, supported 220 household applications for the NJBAP and was successful on 161 properties. In an author conversation with a representative from Woodbridge, they explained that the municipality worked closely with residents to verify program eligibility and facilitate coordination among the residents in the application process. The township also tracked applications and created online maps so that residents could see who had applied. Conversely, the NJ Department of Community Affairs suggested that some coastal areas affected severely by Sandy, including Toms River Township, nonetheless opted out of the buyout program despite having many willing applicants, stating they were not interested in a program that would shrink their tax base.

3. MUNICIPAL BALANCED BUDGET CONCEPTUAL FRAMEWORK

To gain insight into potential barriers to implementation of a buyout program, we first must look at what an efficient or cost-effective program would look like. The neoclassical approach treats a policy intervention as a chance to correct a failure of an unregulated market outcome. In our case, such a policy would provide both municipalities and homeowners the proper incentives to participate when the social benefits of the buyout would exceed the costs. The political economy of these types of decisions often diverges from a first-best policy solution to one that can more accurately describe the political process of policy development and implementation (Oates and Portney 2001). Examples include median-voter models to estimate demand for public goods (Bergstrom and Goodman 1973) and models where the objective function of a policy maker is influenced by interest groups (Keohane et al. 1998). In practice, environmental policy decisions in the U.S. tend to be centralized with the federal government. These decisions may become more decentralized when the public goods in question are local in nature, although evidence is mixed on the efficiency implications of changing the jurisdictional scale of regulations (Banzhaf and Chupp 2010; Dinan et al. 1999). Local decision-makers may also bring in their own set of objectives related to budget concerns (Oates and Portney 2001) or have some constraints imposed by a higher level of government (e.g., anti-deficit provisions). These elements have potential to create adverse incentives, like the principal-agent problem, if local governments have goals that are not aligned with maximizing net benefits of a policy change to their constituents (e.g., maintaining a tax base at the cost of future resilience to natural hazards) or are focused on short-run goals to maximize their own political capital (Healy and Malhotra 2009).

The NJBAP is a multi-jurisdiction policy instrument that uses federal funding but requires participation and coordination by both state and local entities to operate. State and local governments in the U.S. largely function under anti-deficit provisions or balanced budget requirements. Thirty-nine states, including NJ, have either constitutional or statutory requirements for state governments to pass a balanced budget (Poterba 1994). Most major cities also have the same budget rules (Lewis 1994). Therefore, a balanced budget framework may be appropriate for thinking about the determinants of a buyout policy implementation in our setting. All NJ municipalities during our study period (2013-18) were required to comply with NJ's Local Budget Law. This law states all municipal budgets must have "sufficient cash collected to meet all debt service requirements, necessary operations of the local unit for the fiscal year and, in addition, provide for any mandatory payments required to be met during the fiscal year" (New Jersey Division of Local Government Services 2010). Characterizing municipal decisions as operating under balanced budget constraints also has recent support in the literature. Jerch et al. (2023) use a balanced budget framework to examine the impact of hurricanes on local finances.

We proceed by assuming municipalities would make decisions about community resilience to hazard risk following a similar balanced budget model.[6] A key to understanding the spatial pattern of successful buyout locations in NJ may be the choice of municipalities in supporting applications from property owners applying to NJBAP and how many applications they are willing to support. Both components of this decision are important in a balanced budget framework. For example, a municipality may be supportive of a buyout program, but only for a few applications to minimize budget complications. On the other hand, a supporting municipality may see budget advantages to supporting many applications. A municipality may also view balanced budget concerns as a reason not to support the program. To unpack this, consider a framework that suggests a municipality with balanced budget requirements would operate, assuming monotonicity with respect to spending, near where the difference between local expenditures and revenues will be at or near 0:

$$E + rD - (R + \mathrm{G}) = 0 \,. \tag{1}$$

E represents total expenditures on local public goods (e.g., schools, sanitation, fire department) and responses to natural hazards (e.g., beach nourishment, flood mitigation), D is existing municipal debt (e.g., bond payments for school construction, road improvements), r is an interest rate, R is local revenues (e.g., property taxes, fees), and G is government transfers. Given local political dynamics that suggest officials have incentives to allocate funds towards projects with short time horizons with high political returns (Healy and Malhotra 2009), we suppress time dimensions for simplicity (following Jerch et al. 2023). A decision to support applications for a voluntary buyout program and the level of support has the potential to impact each of these components of a municipal budget. A total differentiation of eq. (1) with respect to a buyout support decision (sb) yields the following:

[6] It is possible that a municipal government may operate with a more complex objective function that includes aims like anti-poverty measures, supporting local businesses or maximizing tourism revenue. However, more complex objectives are typically not observable to researchers at the scale and scope of our analysis so we assume that a balanced budget model is a reasonable hypothesis for how municipalities in NJ are likely to make decisions.

$$\frac{dE}{dsb} + \frac{dD}{dsb}r + \frac{dr}{dsb}D - \frac{dR}{dsb} - \frac{dG}{dsb} = 0. \qquad (2)$$

The effect of supporting buyouts on local expenditures ($\frac{dE}{dsb}$) is ambiguous. Expenditures on local public goods may decrease through reduced services if the buyout program removes housing (e.g., one less street to maintain sewer lines and provide police/fire service). This outcome likely relies on a clustered approach to buyouts, since the public goods nature of municipal services suggests this would only occur if an entire street or neighborhood is removed. Isolated buyouts (i.e., one home on a given street) would not change maintenance costs as the town would still be providing a baseline level of services to other nearby residents. On the other hand, it is possible that such expenditures could increase if bought-out properties become public spaces that require management and maintenance. Expenditures on hazard mitigation are likely to decrease if a municipality supports buyout applications for a few potential reasons. First, it may reduce the number of risk-prone properties and, therefore, the amount a municipality must spend to maintain infrastructure and services in these areas. For federal flood damage reduction projects or beach nourishment programs, there is usually an expectation of a state/local cost share between 35 to 50 percent (Congressional Research Service 2019). Second, towns may be able to reduce expenditures on personnel/time dedicated to managing hazard risk and disaster claims if chronically damaged properties are bought out and converted to open space.

Municipal debt and interest rates may also play a role in the decision to participate in a voluntary buyout program ($\frac{dD}{dsb}$; $\frac{dr}{dsb}$). Municipalities with larger debt from bond repayments may see value in participating in the buyout program to limit future liabilities and improve future borrowing prospects (i.e., new school construction). This latter point is demonstrated by recent actions by major insurers and credit agencies, suggesting climate resilience will play a role in future borrowing efforts of cities and towns (e.g., Moody's 2017). Conversely, municipalities with larger debt may be less likely to participate as they may be more sensitive to changes in revenues that could occur from supporting buyouts, as local revenues tend to be funded mainly by property taxes (regardless of debt levels). Revenue is a function of local tax rates, property values, and the number of properties, and support for a voluntary buyout program would likely reduce local revenues as the program removes parcels from the tax base ($\frac{dR}{dsb} < 0$). Municipalities in New Jersey are highly dependent on property taxes for local revenue (89 percent on average; Table 1), so potential revenue effects could be a significant impediment to buyout support under a balanced budget model. Local governments may be able to offset potential revenue losses from having fewer taxable units due to a buyout program by raising property tax rates on remaining homes.

Lastly, experience with government transfers for community hazard resilience may also influence if and how a municipality supports buyouts ($\frac{dG}{dsb}$). While funds for a buyout are in itself a government transfer, the act of moving land from housing to open space could affect other transfers received.[7] Municipalities where *ex-ante* transfers are more prevalent may be less likely to support buyouts due to the belief that risk is being mitigated through existing programs. On the other hand, such municipalities may be more apt to support voluntary buyouts after realizing benefits related to other *ex-ante* mitigation efforts. If a municipality believes that its residents may be compensated *ex-post* for damages as evidenced by a high number of aid recipients from previous hazard events, it may, conditional on the same level of damages, decrease the probability that a town would participate in *ex-ante* efforts like a voluntary buyout program. The combination of these potential budgetary impacts is likely to contribute to a municipality's decision to support voluntary buyout applications from their residents.

4. DATA

The conceptual framework above illustrates an important decision pathway that is necessary for a successful buyout in the NJBAP and suggests multiple potential factors that may affect those decisions. The ideal setting to evaluate the effect of those factors empirically, given the inability to do a randomized experiment, would be to leverage a panel of observations of buyouts across similar municipalities with different degrees of buyout support and an exogenous shock (e.g., Hurricane Sandy) that provided new hazard information (Hallstrom and Smith 2005). In this paper, data availability limits our capacity to estimate the effects through a causal lens. First, our data on locations and timing of successful buyouts obtained from the NJDEP includes all properties whose buyout processes were completed between 2013 and 2018, the six years after Hurricane Sandy. Although NJBAP started in 1995, it was not well funded by FEMA and the NJ state government

[7] *Ex-ante* transfers are designed to mitigate hazard risk before an event occurs (e.g., FEMA HGMP provides homeowners with funds for ex-ante mitigation efforts, such as elevating structures in flood-prone areas) whereas *ex-post* transfers provide direct financial support to those impacted by a natural hazard (e.g., FEMA IHP).

until after Sandy, and the NJDEP could not provide similar data from the limited number of buyouts prior to 2013. Second, our key variables of interest for municipal budgets lack the temporal variation we would need to estimate a panel model because they come from the Census of Government from the U.S. Census Bureau, which did not record data between 2012 and 2017.[8] We use the 2017 data in our estimation and both the 2012 and 2017 data to show how variables change over time as summary statistics. Third, the acquisition process is often lengthy, spanning multiple time periods, and the program requirement for municipal support is likely a single decision to support buyouts generally rather than a decision that repeats each period. Given these limitations, we treat the data as cross-sectional and use the available data and rich context obtained through authors' correspondences with NJ stakeholders to shed light on the complex decision-making process surrounding government buyout programs. We believe our current focus on the NJ program is a meaningful first step in understanding potential barriers to managed retreat programs in high-risk coastal areas and may spur future research investigating causal effects of the correlations found here.

Data provided by NJDEP includes the location and closing date of 683 properties with successful buyouts across 14 municipalities from 2013 to 2018 (Figure S1 in the Online Appendix). We do not observe where individuals move after a buyout or the price received. We follow our conceptual framework and collect data on potential factors influencing buyout activity at two spatial scales: 1) the municipality and 2) Census tracts within each municipality. NJ contains 564 municipalities. A census tract is an area roughly equivalent to a neighborhood (Klaiber et al., 2017) established by the U.S. Census Bureau and encompasses a population between 2,500 to 8,000 people. New Jersey contains 2,010 census tracts, of which 1,936 contain data suitable for our analysis.

For expenditures (E), we use the Census of Government data to obtain expenditure on public goods as a share of total revenues. The public goods included in the expenditure data are elementary and secondary education, local fire protection, parks and recreation, police protection, welfare payments, sewerage, and solid waste management. To measure characteristics that affect expenditures on natural hazards, we calculate the distance to federal beach nourishment projects (common in NJ), calculated in ArcMap as a straight line from census tract neighborhood to the

[8] Available at https://www.census.gov/programs-surveys/cog.html.

closest beach that has been nourished since 1990.[9] The beach nourishment data was obtained from the Program for the Study of Developed Shorelines at Western Carolina University.[10]

For debts (*D*), we obtain outstanding long-term debt as a share of total revenues for the Census of Government to measure the degree of financial constraint due to the debt servicing across municipalities.[11, 12] To account for variation in revenue (*R*) composition across municipalities and neighborhoods, we use total revenues and property taxes as a share of total revenue for each municipality from the Census of Government and parcel-level tax data from the NJ Office of Information Technology Open Data Center. Variables included in the latter dataset include average property tax payments and average assessed property values. We also use the shares of residential, vacant, and owner-occupied housing units in each area as additional controls. Government transfers (*G*) like *ex-post* disaster aid and *ex-ante* mitigation investment, could also affect the buyout participation decision and the buyout outcome. To account for *ex-post* transfers, we obtained the number of households per municipality and neighborhood that have been approved for payments from FEMA's IHP program.[13] This federal aid applies to homeowners, renters, and business owners in designated counties who sustained damage to their homes, vehicles, personal property, businesses, or inventory because of a federally declared disaster. Disaster assistance may include grants to help pay for temporary housing, emergency home repairs, uninsured and underinsured personal property losses, and medical, dental, and funeral expenses caused by the

[9] The distance from beach nourishment at the municipality level is the average of the distances from the census tracts within the municipality. Given variation in sizes and shapes of census tracts and municipalities, measurement error may be a concern. We also measure the municipal distance as an average of all individual parcels and this average is very similar to our simpler measurement and our results are robust to either measurement.

[10] Available at http://beachnourishment.wcu.edu/.

[11] We also obtained municipal bond ratings for 300 municipalities (out of 564 municipalities) in NJ from Moody's to include as an explanatory variable. We exclude this variable from our analysis as 1) not all municipalities issue municipal bonds; 2) there is limited variation in rating across municipalities in NJ (in the rating scheme from Aaa (strongest creditworthiness) to C (weakest), about 60 percent of municipalities have rating higher than Aa3 (very strong), and more than 93 percent with ratings higher than A3 (above average)); and 3) there is a potential endogeneity issue due to reverse causation between buyout decision and bond rating. Data is accessible with a free account at https://www.moodys.com/researchandratings/market-segment/u-s-public-finance/local-government.

[12] While we only observe long-term debt in this setting, it is possible that some municipalities may be forward looking about debt financing and investments in resilience. As such, expected debt may be a better measure here (if observable). Therefore, our measure of current debt may be subject to some measurement error.

[13] FEMA also provides Public Assistance (PA) grants to the areas that received a Presidential declaration of an emergency. We focus on IHP instead since it is directed toward private houses for repair and reconstruction, as opposed to projects under PA, which are directed toward public infrastructures such as repairing roads and bridges and debris removal. Furthermore, PA data is only available at a scale that is more aggregated (i.e., county) than our units of analysis.

disaster, along with other serious disaster-related expenses. For *ex-ante* transfers, we collected the number of homes per municipality and neighborhood that have been physically elevated to mitigate flood risk through FEMA's HGMP.

To control for homeowner decisions in our models, we include the count of applications to NJBAP per municipality and an indicator of at least one application at the municipality level in our census-tract-level data (note that the application count is only available at the municipality level). We also include the number of residential parcels per neighborhood that fall within FEMA's Special Flood Hazard Area (SFHA) and the number of parcels within areas inundated by storm surge from Hurricane Sandy using the USGS's Storm Surge Sensor data. These variables indicate the extent of households that are currently exposed to flood risk and likely qualify for the NJBAP. For future hazard risk, we calculate the number of residential parcels in each municipality and neighborhood likely to be impacted by 6' of sea-level rise as projected by NOAA's Office of Coastal Management Digital Coast.[14] We also collect demographic information to include as controls, such as racial composition, population with children under 18, population of 65 years and older, foreign-born population, and households below the poverty line from the American Community Survey 5-year estimates (2013-2017). We also include the average crime index (Esri Crime Indexes) from 2010 that compares the average local crime level to that of the entire U.S.[15] Data reported by zip code are assigned to a census tract neighborhood using a ratio of residential properties from a Department of Housing and Urban Development (HUD) and FEMA data crosswalk.

Inspection of summary statistics from the data reveals several important contrasts. Table 1 displays municipal-level statistics for all locations in NJ (col. 1), only municipalities that supported buyouts (col. 2), and only municipalities deemed high-risk that did not support buyouts (col. 3). Municipalities that supported buyouts (col. 2) have lower average property values, higher municipal tax rates and higher levels of intergovernmental transfers than other municipalities across NJ. The municipalities with buyouts are located further away from a recently nourished beach compared to municipalities deemed high-risk that did not support buyouts. As expected, municipalities with buyouts had significantly more applications on average (77) than

[14] Available at https://coast.noaa.gov/digitalcoast/.
[15] A crime index of 100 is a national average, and the local crime index measures the relative overall crime rate in each census tract. Therefore, a lower crime index indicates a relatively safer neighborhood.

municipalities without buyouts (9). Table 2 shows summary statistics across different sets of neighborhoods (census tracts). Column (1) contains all census tracts in New Jersey, column (2) is census tracts that are either in a FEMA flood zone or impacted by storm surge from Sandy (i.e., broadly eligible for buyouts), column (3) is a subset of (2) with no observed buyouts, and column (4) is a subset of (2) where at least one property was purchased through NJBAP. At the neighborhood level, we see statistically significant differences in fifteen variables of note. Census tracts with observed buyouts tend to have fewer residential parcels and lower shares of vacant parcels, along with lower assessed property values. Neighborhoods with buyouts also had higher average NFIP payments but fewer applicants receiving FEMA post-disaster IHP assistance. These neighborhoods also had larger shares of family households, black/Hispanic residents and foreign-born population relative to high-risk areas that did not have buyouts. Interestingly, areas with buyouts also had lower share of parcels affected by Sandy and lower expected impacts from future SLR than high-risk areas without buyouts. Table S1 in the Online Appendix provides similar comparisons between municipalities without buyouts but with multiple homeowner applications (col. 2) and municipalities with successful buyouts (col. 3). For those towns without buyouts but willing homeowners, we see higher residential assessed property values and higher dependence on property tax as a share of total revenues compared to buyout municipalities. There is also a higher percentage of parcels exposed to flood risk and future SLR, and higher *ex-ante* and *ex-post* government transfers in municipalities that did not support buyouts.

5. EMPIRICAL ESTIMATION

The goal of our empirical analysis is to find a broad set of evidence about the budgetary factors that may impact a municipality's decision to support a voluntary buyout program. While the results of our analyses should be viewed as descriptive, we take steps to minimize bias in our estimates from omitted variables through the addition of key demographic variables, from potential endogenous controls by omitting them from model specifications, and from selection bias by modeling the decision as a two-stage process. We begin by regressing the number of successful buyouts in a municipality on variables representing the components of a municipal government balanced budget: revenues, debt, expenditures, and government transfers. Since the number of buyouts is count distributed, ordinary least squares estimation would likely be biased. We estimate a negative binomial model at two spatial scales – the municipality and neighborhoods (census tracts) within a municipality – as follows:

$$y_p = \beta_1 R_p + \beta_2 D_p + \beta_3 E_p + \beta_4 G_p + \beta_5 SFHA_p + \beta_6 SLR_p + \gamma X_p + \varepsilon_p \,, \quad (3)$$

where y_p is buyout counts for location *p*, which is either a municipality (*m*) or neighborhood (*n*) (i.e., $p = \{m, n\}$). R_p represents revenue-related items such as total revenues, property taxes as a share of total revenue, assessed housing values, average property taxes paid, and shares of residential, vacant, and owner-occupied parcels. D_p is long-term debt as share of total revenue, and E_p is expenditure-related items such as public goods expenditure as share of total revenue. G_p represents government transfers variables, such as the number of houses elevated under FEMA's HGMP (*ex-ante* investments) and number of households approved for IHP (*ex-post* disaster aid). Since shares of property tax revenue, long-term debt, and public goods expenditures are all reported at the municipality level, these variables are scaled to each census tract based on the number of residential parcels for the property tax share and the number of residents for the other two variables for the neighborhood-scale models. $SFHA_p$ is the share of residential parcels in FEMA flood zones or affected by Sandy and SLR_p is the share of parcels in location *p* within areas vulnerable to 6-feet of SLR. X_p includes a count of buyout applications at the municipality level (indicator for at least one applicant at the census tract level) to account for unobserved factors that may affect buyout effort, such as implicit pressure from the homeowners on the municipal government.[16] Furthermore, economic and demographic variables that could account for other unobservable factors that affect the buyout outcome are included in X_p, including shares of foreign-born population to account for citizenship requirements attached to FEMA funding (Grube et al. 2018). We estimate eq. (3) at the municipal- (*m*) and then the neighborhood-scale (*n*), which expands the observations in the cross-section from 506 to 1,936.

[16] One concern stemming from observations in our summary statistics (Table 1) is that municipalities with buyouts have similar average pre- and post-Sandy assessed values while those without buyouts have much higher assessed values post-Sandy. This difference may indicate that higher value homes continue to increase in value ex-post while lower valued homes remain stagnant and therefore fewer applications on average from areas with higher valued homes. It is these market dynamics and homeowner incentives that we attempt to control for here with application counts. We also include Figure S2 panel B in the online appendix showing that we do observe applications from a number of municipalities with higher valued properties, which may partially alleviate this concern.

Next, we estimate a set of two-stage models to better characterize the structure of decision making about the buyout program and mitigate concerns about selection bias. The decision structure for a successful application to the NJBAP program is dependent on municipal government actions: a choice to support applications to the program and then conditional on that support, how many applications and from what locations does the municipality partner with the state program to successful completion. Two-stage models have the advantage of allowing different mechanisms to affect the support and amount decisions. We start with a model with a binary dependent variable in the first stage (municipal support) and a count data model with positive values (buyout counts) in the second stage. Our unit of observation is neighborhoods (n) that are targeted in the outcome model, not the municipalities. The first stage model estimates the probability of a neighborhood being selected by a supporting municipality, given the characteristics of the neighborhood. This is equivalent to the municipalities choosing to support the program, given the characteristics of their neighborhoods.

We first estimate a hurdle model, which assumes the support decision and the buyout count amounts are independent, conditional on explanatory variables. The first part that specifies a hurdle component uses a binomial logit to represent the binary municipal support decision. The second stage after the hurdle is crossed uses a truncated negative binomial model with positive buyout counts as the dependent variable. For the hurdle model, the observed value of buyout count y_n is characterized by the relationship, $y_n = s_n h_n^*$, where selection variable s_n is defined as:

$$s_n = \begin{cases} 1 \; if \; e_n \omega + \varepsilon_n > 0 \\ 0 \; otherwise \end{cases} \tag{4}$$

where e_n is a vector of explanatory variables, ω is a vector of coefficients, and ε_n is a standard normal error term. The latent variable h_n^* is only observed when $s_n = 1$, upon which the second-stage outcome model is estimated for the positive count part.

The second two-stage model we estimate addresses concerns about sample selection and explicitly allows correlation between the support and amount decisions, helping to avoid inconsistent estimates of coefficients of interest. We use a two-step sample selection model following Heckman (1979) estimated as a type II Tobit model. The standard two-stage model is a binary “in or out” choice followed by the outcome model of density (how much once “in”). In our setting, the outcome is not only the overall density (how many buyouts) but also the location (how many buyouts in what neighborhoods), so we define the first-stage support equation as follows:

$$z_n^* = w_n \gamma + u_n \qquad\qquad z_n = \begin{cases} 1 \; if \; z_n^* > 0 \\ 0 \; if \; z_n^* \leq 0 \end{cases}, \tag{5}$$

where z_n^* is the latent variable measuring the underlying propensity for neighborhood n to be in a municipality that supports the buyout program, z_n is the binary variable indicating whether the neighborhood belongs to a supporting municipality or not, w_n is a vector of explanatory variables determined from our conceptual framework, γ is a vector of coefficients to be estimated, and u_n is a vector of unobservable factors.[17]

Our second-stage outcome equation is:

$$y_n = \begin{cases} x_n \beta + \epsilon_n \; if \; z_n = 1 \\ \quad none \; if \; z_n = 0 \end{cases}, \tag{6}$$

where y_n is the number of bought-out properties in each neighborhood, x_n is a vector of explanatory variables, β is a vector of coefficients to be estimated and ϵ_n is a vector of unobservable factors. We operationalize the support equation (eq. 5) by regressing an observed binary indicator of whether each neighborhood is within a supporting municipality on variables representing key expenditure, debt, revenue, government transfer, and demographic variables. In the outcome regression (eq. 6), we use a similar set of explanatory variables. For the Heckman specification, we omit property tax, long-term debt, and expenditures on public goods as shares of total revenues, along with distance to the nearest nourished beach, to meet the exclusion restriction for the sample selection model. The first three items are excluded as these variables are measured only at the municipality-scale and are likely to predict support but are not likely to affect the buyout density and location as they do not vary across neighborhoods. The distance to the nearest nourished beach is also excluded because beach nourishment projects most often happen at the scale of a municipality or larger, again likely only affecting the support decision.

[17] Due to the nature of the data described in Section 4, we treat our data as a cross-section and do not have a time component.

6. RESULTS

Table 3 presents results for the negative binomial specification where the dependent variable is number of buyouts at different scales of the observation unit: municipality in column (1) and census tract in columns (2) and (3). We focus our discussion on census tract level results as municipality-level results lack precision in estimates due to small sample size, with col. (3) being our preferred specification.[18] First, revenue-related factors like higher assessed property values, property tax as a share of total revenues and share of residential parcels are all negatively associated with buyout counts.[19] This provides suggestive evidence that factors that directly impact municipal revenues from property taxes may be a barrier to adopting managed retreat policies. Long-term debt share has a positive effect on buyout outcomes, suggesting that local governments reliant on long-term debt may be reacting to new pressure from credit rating agencies and financial lenders that require transparency and more forward-looking climate adaptation strategies. For the government transfer variables, the number of elevated homes is negatively correlated with buyouts, indicating a potential crowding out effect. It is reasonable to believe that government transfers endogenously affect buyout decisions (e.g., due to reverse causality), but in col. (2) that excludes these controls, the sign, magnitude, and statistical significance of all other covariates do not change in any meaningful way. As expected, an indicator for at least one buyout are positively and significantly associated with buyout counts.

When looking at the impact of current and future risks of inundation, we find that as the number of parcels in FEMA's SFHA increases, buyout counts are likely to increase. This impact is likely consistent with saliency of current risk as it may capture aspects of households familiar with government programs (i.e., awareness of public assistance and competency for navigating bureaucracy) due to NFIP requirements in these areas. Notably, there is a negative effect associated with having more homes vulnerable to 6 feet of SLR. These last two points taken together suggest buyouts increase in areas with high current flood risk and decrease in areas with high future

[18] Online Appendix Table S2 has full estimation results with all variables across different specifications including a Poisson model. We used a log likelihood ratio test to compare Poisson and negative binomial model results. The test strongly suggests the negative binomial model offers a better fit than the Poisson model.

[19] The variable property-tax-as-share-of-revenue does have limited variation across our sample (mean 0.89, standard deviation 0.14), suggesting most municipalities in New Jersey are heavily dependent on property taxes for their revenue. These results suggest that even small variation in this share may impact municipal decisions on participating in the buyout program.

inundation risk. This is consistent with the findings of Healy and Malhotra (2009) that municipal government decisions with budget implications often focus on short time horizons. These results may also offer insights into homeowner decisions, as they support the ideas that short-run risk may be salient, but misperceptions of long-run risk remain common (Bakkensen and Blair 2022; Bakkensen and Barrage 2022).

The results from our two-stage models are displayed in Table 4.[20] Our descriptive results here suggest that expenditure, debt, and revenue components of a municipal budget are likely to have an impact on the support decision for buyouts and, in general, are consistent with findings from the single-stage models. We see that municipalities with a higher dependence on property taxes for local revenue and higher assessed property values are less likely to support the program. These findings match with a balanced budget framework and suggest losing part of a tax base is potentially a large barrier to participation in the state buyout program. If residents are willing to participate in the buyout program and help make their community more resilient to natural disasters, but the municipal government chooses not to participate, this may be indicative of a principal-agent problem with respect to coastal resilience investments.

There is also a consistent negative and significant effect on support for the buyout program in both models as the percentage of municipal expenditures on public goods increases. Municipal support is positively correlated with homes at current flood risk in the hurdle model and buyout counts in both models. Municipal support is negatively correlated with more homes in SLR areas in the Heckman model. Debt impacts were significant in the Heckman model and suggested that towns with larger financial constraints due to their outstanding long-term debt are more likely to participate. In the hurdle model, both *ex-post* IHP aid and *ex-ante* home elevation variables do not have a significant effect on the first-stage outcome. In the second-stage, *ex-post* disaster aid is positively correlated with buyout counts and *ex-ante* home elevation is negatively correlated, consistent with Table 3 results. In the Heckman model, municipal support is negatively correlated with *ex-post* aid and positively correlated with *ex-ante* transfers. This suggests a different story – municipalities with more experience with *ex-ante* transfers are more likely to support buyouts (another *ex-ante* program) and less likely to support buyouts with more experience with *ex-post*

[20] Online appendix Tables S3 and S4 show full estimation results for Hurdle and Heckman, respectively, with several different specifications as robustness checks.

disaster aid. Notably, in the second stage, buyout counts are again positively correlated with *ex-post* aid.

To summarize, there are multiple key consistencies in results that hold across model specifications. The revenue impacts suggest a potential principal-agent problem, where municipalities may be making community resilience decisions based on property tax considerations. Coastal towns like those in NJ that are dependent on property taxes for revenue and have high assessed property values are less likely to see successful buyouts. Expenditure and debt considerations are also likely to play a role in buyout support and success. Current risk increases buyout success, while buyouts in areas subject to future SLR are less likely. We find some mixed evidence on the effects of government transfers on buyouts. Taken together, these descriptive results suggest that various elements of municipal budget considerations may play a significant role in the success or failure of voluntary managed retreat policies.

7. DISCUSSION

Given the potential for significant economic damages in the future due to SLR and the amplification of tropical and extratropical cyclone activity (Hsiang et al. 2017), retreat from coastal hazards is likely to be an important policy tool for local adaptation planning. Our study highlights the importance of understanding the local government decision processes in relation to managed retreat policy programs. Our results find evidence that revenue effects may be a significant barrier to adoption of managed retreat. Previous work has shown that coastal natural amenities (e.g., wide beaches, ocean views) are contributing factors in income stratification, anchoring higher-income households to these locations (Smith and Whitmore 2020). Our result reveals that this attachment is possibly amplified by the municipalities' financial dependence on these properties with higher assessed values for revenues. A voluntary buyout program may not be successful in towns dependent on property taxes for revenue and where households may have the financial ability to adapt privately.

There are a few possible options for minimizing this revenue problem. First, a municipality could raise property tax rates on remaining households. Second, local governments could encourage affected households to relocate to undeveloped land away from the hazard within the same municipality, thus at least partially retaining its tax base. Third, a municipality may choose to retreat collectively and consolidate with neighboring communities. Fourth, municipalities could actively change their objective function by accounting for the benefits of retreat, such as positive effects on the remaining parcels from newly created buffers that protect them from hazard risk along with the potential for increased amenity values from new open space and a net saving from avoided expenditures to protect houses from future hazards. The change in estimating credit risks among insurance companies and credit agencies, which increasingly account for climate risk reductions, may become a powerful catalyst for this option.

It is important to understand the significant economic and social damages from coastal hazards that are projected to increase with climate change. Our empirical focus on a unique state-level buyout program reveals substantial issues that may prevent current programs from reaching their objectives to reduce risk and make coastal communities more resilient to natural hazards. The New Jersey Blue Acres program is the first such program in the nation, with Louisiana (LA SAFE), New York (NY Rising Buyout and Acquisition Program), and Harris County, Texas (Home Buyout Program) also focused on retreat as an adaptation pathway. As more states in the U.S. and countries around the world confront the realities of SLR and increased coastal storms, retreat through buyout programs represents a critical land-use tool to adapt. The economic lessons and challenges discussed here can help the design and implementation of these future programs.

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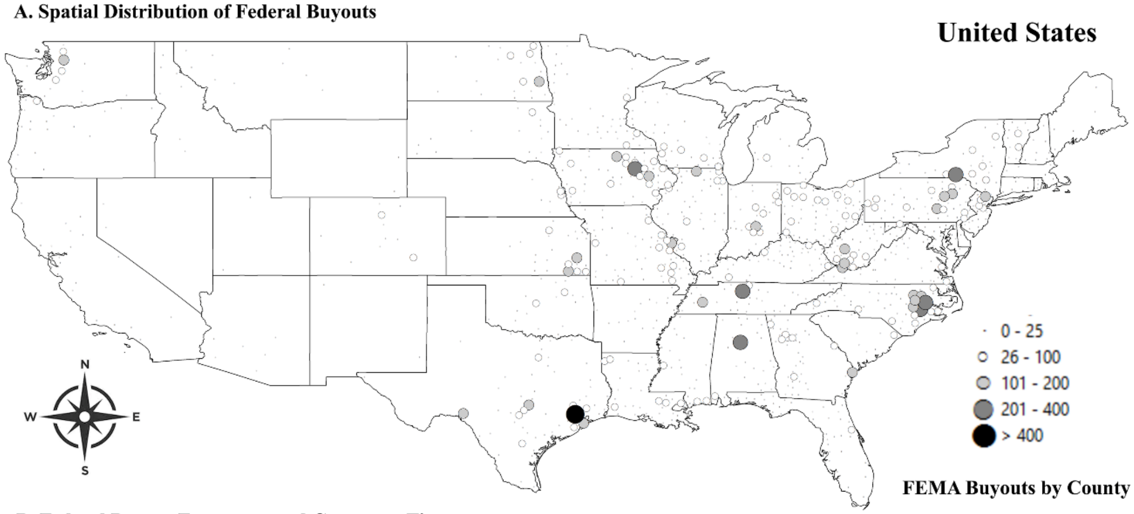
A. Spatial Distribution of Federal Buyouts



B. Federal Buyout Frequency and Costs over Time

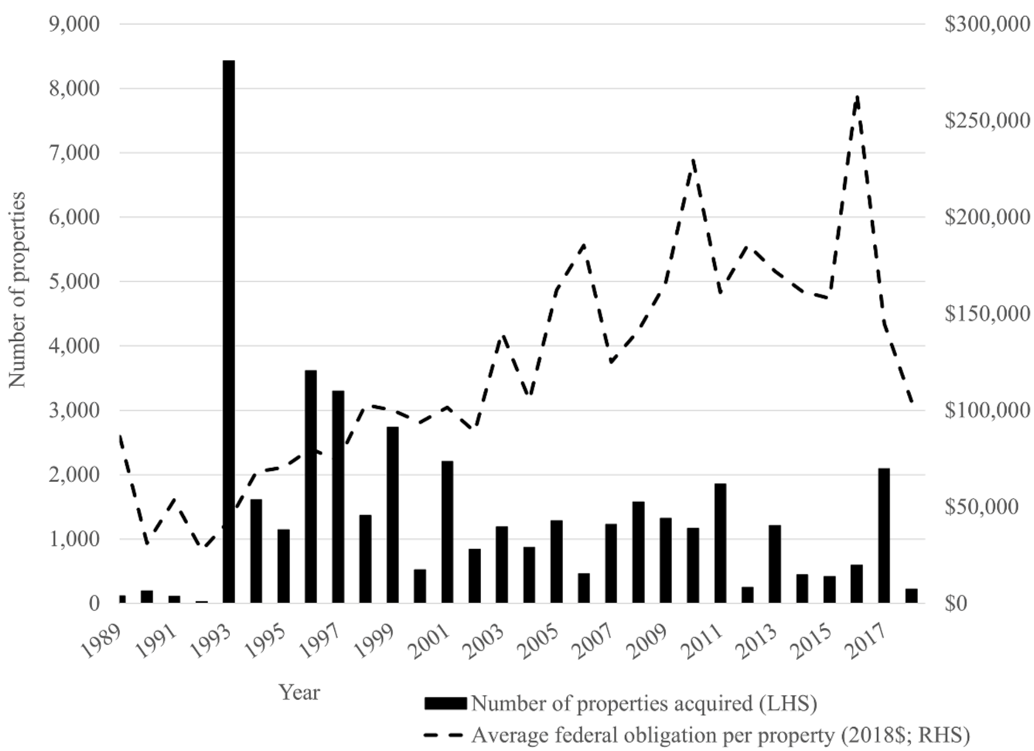


Figure 1. Federal Buyouts in the United States: 1989 – 2018

Note: Panel A shows the national distribution of federal buyouts and the general lack of buyouts in coastal areas of the United States. In Panel B, the left y-axis represents number of properties acquired (i.e., what FEMA defines as "acquisition of private real property" through their Hazard Mitigation Assistance Program), and the right y-axis shows the average cost to acquire each property.

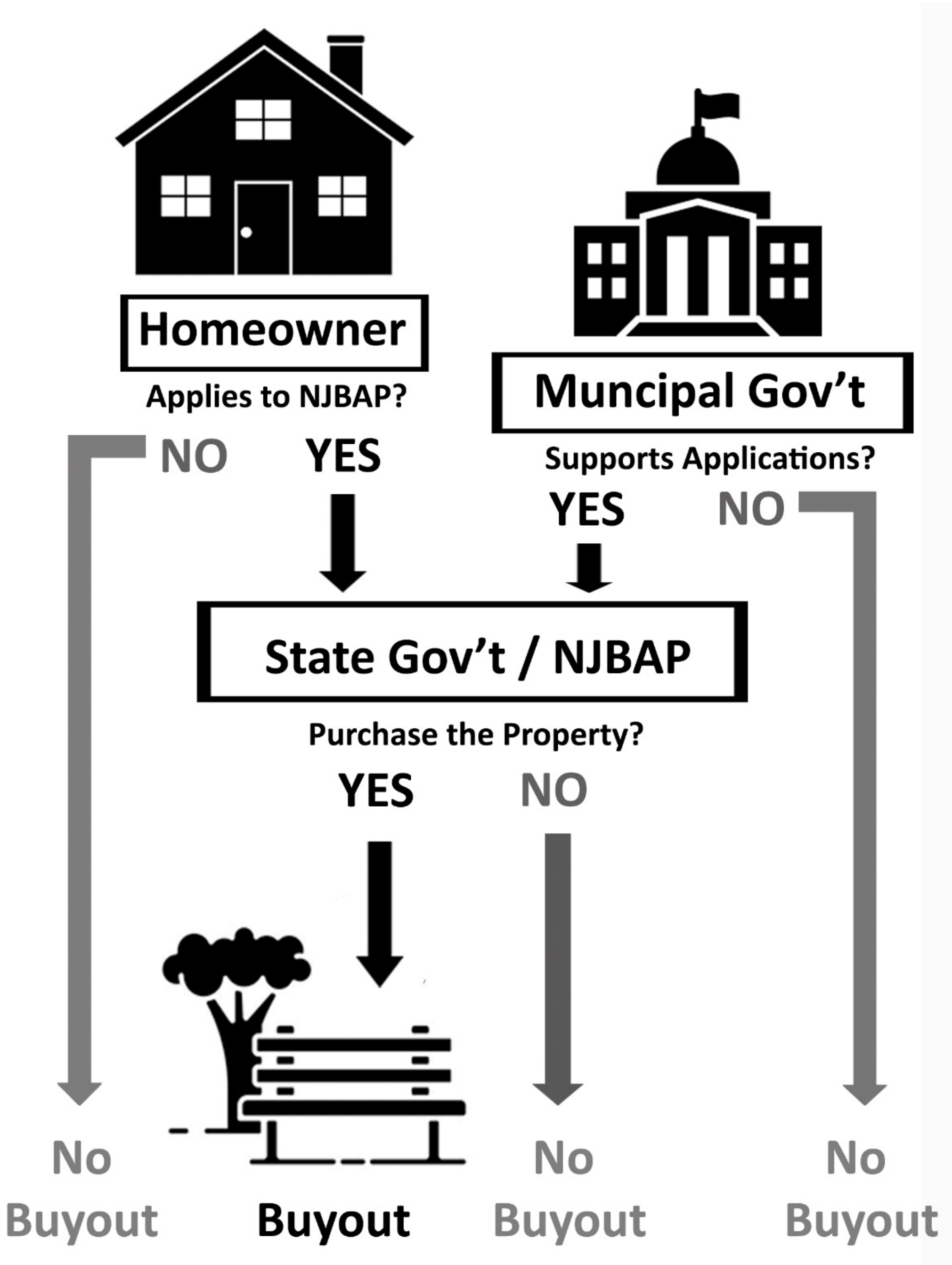


Figure 2: New Jersey Blue Acres Program Process and Potential Outcomes

Note: This figure illustrates the potential outcomes of a buyout application. In order for a buyout to occur, a homeowner must voluntarily apply to NJBAP and the municipality must generally support buyout applications from their residents. If both events occur, then the state government decides whether to proceed with the buyout based on their own criteria for selecting parcels for the program.

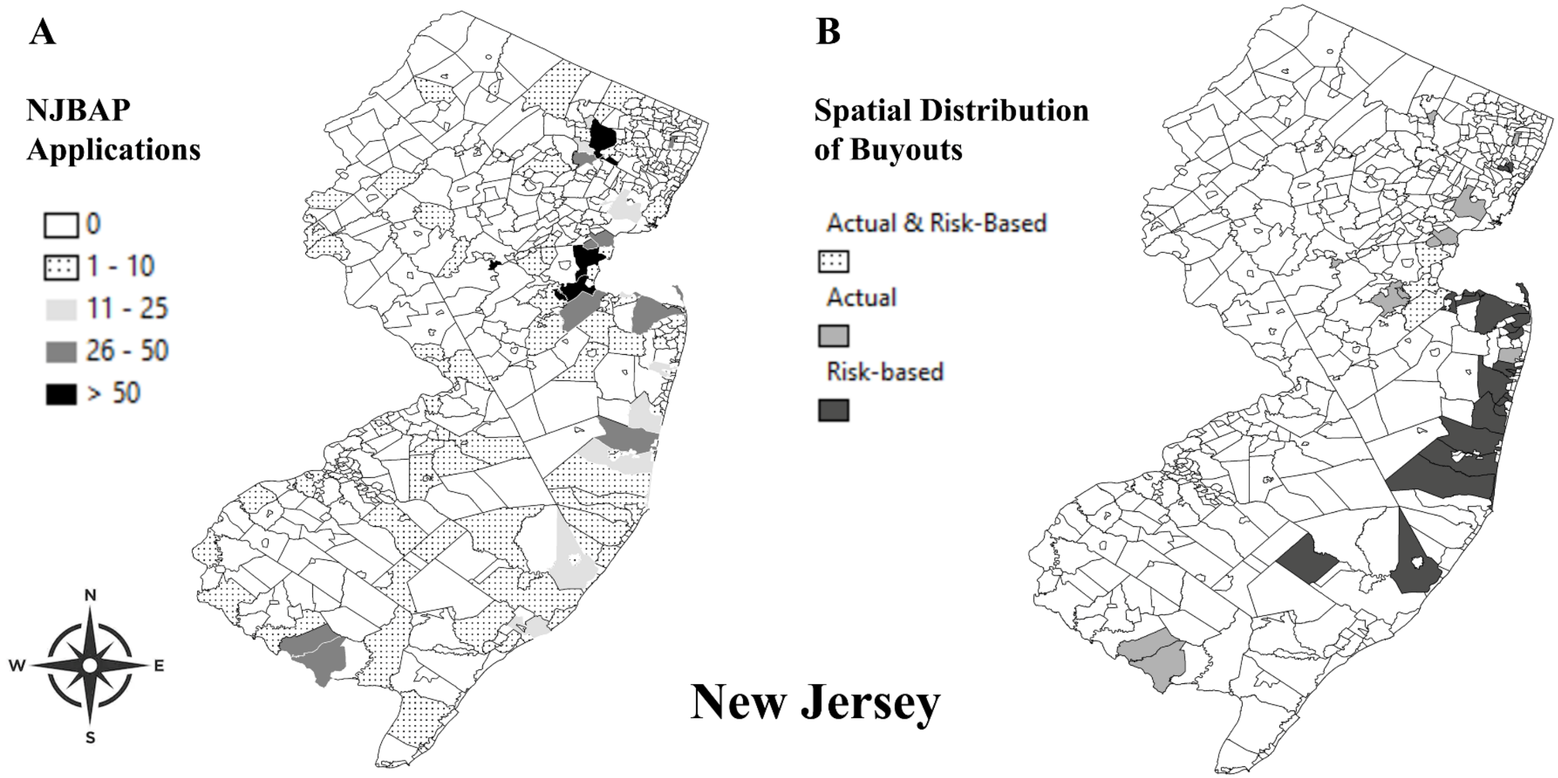


Figure 3: New Jersey Blue Acres Program Location of Applications and Buyouts

Note: Panel A shows the count of NJBAP applications by municipality. Panel B depicts location of municipalities deemed at risk under NJBAP compared to where actual buyouts occurred. The risk-based buyout candidates are generated by the authors based on municipalities that contain 1) areas within the FEMA 1 percent flood zone, 2) zipcodes with >$10,000 average FEMA inspected damage from Sandy and >30 FEMA applicants who were approved for FEMA's Individuals and Households Program (IHP) assistance, and 3) neighborhoods that have >80 percent owner-occupying housing units.

Table 1. Summary Statistics for Municipalities in New Jersey by Buyout Outcome

	(1) All municipalities (N = 565)	(2) Municipalities w/ Buyouts (N = 14)	(3) Municipalities w/o buyouts, high risk (N=22)	(4) Significant Difference btw. Col (2) - (3) at 10%
Total revenues (TR) ('000$)	21,587 (40,640)	61,959 (100,263)	26,671 (25,632)	N
TR per HH ('000$)	10.09 (48.13)	4.99 (3.20)	4.85 (3.80)	N
Long-term debt share of TR	1.18 (6.64)	0.71 (0.42)	0.71 (0.73)	N
Property tax as share of TR	0.89 (0.14)	0.84 (0.19)	0.91 (0.09)	N
Public goods expenditure share of TR	0.54 (2.05)	0.41 (0.19)	0.45 (0.17)	N
Intergov revenues-federal ('000$)	904 (4,746)	2,004 (3,880)	492 (1,082)	N
Intergov revenues-federal per HH ('000$)	0.17 (0.95)	0.13 (0.17)	0.09 (0.30)	Y*
Total outstanding long-term debt ('000$)	18,593 (47,582)	58,161 (111,118)	15,630 (13,098)	N
Total outstanding long-term debt per HH ('000$)	6.87 (30.39)	3.86 (4.00)	2.82 (2.86)	N
Δ long-term debt 2012-17 ('000$)	-2,460 (21,553)	-14,547 (50,835)	-11,060 (30,633)	N
Δ total revenues 2012-17 ('000$)	2,755 (17,458)	-2,884 (25,224)	4,817 (7,609)	N
Δ property tax 2012-17 ('000$)	2,923 (15,228)	7,387 (10,702)	4,761 (7,261)	N
Δ property tax share of TR 2012-17	0.01 (0.09)	0.06 (0.10)	0.02 (0.06)	N
Δ debt share of TR 2012-17	0.08 (6.20)	-0.07 (0.40)	-0.25 (0.89)	N
Δ intergov revenues – fed. 2012-17 ('000$)	-368 (6,159)	-9,697 (35,287)	-229 (1,297)	N
Avg. property value in 2011 (‘000$)	347 (306)	186 (109)	374 (229)	Y
Avg. property value in 2018 (‘000$)	358 (309)	187 (109)	407 (278)	Y
Δ Avg. property value (‘000$)	10 (78)	1 (52)	32 (88)	N
Municipal tax rate in 2011	1.02 (3.99)	1.29 (0.74)	0.68 (0.42)	Y
Municipal tax rate in 2018	0.94 (1.09)	1.53 (0.91)	0.76 (0.48)	Y
Δ municipal tax rate	-0.07 (3.57)	0.24 (0.29)	0.08 (0.18)	Y
Avg. bond rating (1-14, smaller the better)	4.29 (2.22)	4.10 (2.60)	4.38 (1.67)	N
Share of bond rating upgrade	0.23 (0.42)	0.10 (0.32)	0.17 (0.38)	N
Share of bond rating downgrade	0.17 (0.38)	0.30 (0.48)	0.28 (0.46)	N
Number of buyout applications	3.14 (18.55)	76.64 (82.92)	8.73 (11.36)	Y
Dist. closest beach recently nourished (km)	37.56 (22.27)	22.86 (17.05)	9.75 (12.43)	Y

Note: Standard deviations in parentheses. Col. 1 contains summary statistics for all municipalities. Municipalities where a buyout occurred are shown in Col. 2. Col. 3 include municipalities deemed at high risk but did not participate in the buyout program. Col. 4 displays if the observed differences in characteristics between col. 2 and col. 3 are statistically significant at 10 percent confidence level based on Wilcoxon rank sum test and t test. When the results of the two tests contradict (indicated as “*”), we based our decision of which result to report on the histogram of sample distributions. Long-term debt, revenues, and government transfers are all for the year 2017. For average bond rating, we assigned ascending numbers from the highest bond rating (Aaa: 1) to the lowest rating (Ba3: 14) and calculated an average for each group. Share of bond rating upgrade (downgrade) is the percentage of municipalities in each group whose municipal bond rating has been upgraded (downgraded) in the last 20 years.

Table 2. Summary Statistics for Census Tracts (Neighborhoods) in New Jersey

	(1) All Census tracts (N = 2,009)	(2) High-Risk Census tracts (N = 766)	(3) High-Risk, No Buyout ((N = 737)	(4) High-Risk, Buyout (N = 29)	(5) Significant Difference btw. Col (3) – (4) at 10%
# of bought-out properties	0.34 (4.26)	0.88 (6.86)	0.00 (0.00)	23.17 (27.43)	Y
# of residential parcels	1,222 (756)	1,375 (824)	1,384 (831)	1,146 (575)	Y*
Share of residential parcels	0.73 (0.20)	0.71 (0.20)	0.71 (0.20)	0.64 (0.22)	N
Share of vacant parcels	0.10 (0.11)	0.13 (0.15)	0.13 (0.16)	0.08 (0.07)	Y
Avg. net assessed value ('000$)	274 (217)	298 (239)	304 (241)	153 (95)	Y
Δ net assessed value, 2012-2017 (‘000$)	10.1 (88.4)	5.9 (96.1)	6.2 (97.7)	-3.1 (39.1)	N
Avg. property tax payment ('000$)	10.2 (14.5)	9.3 (5.7)	9.2 (5.5)	11.3 (10.1)	N
Share of owner-occupied units	0.57 (0.26)	0.57 (0.24)	0.57 (0.24)	0.60 (0.23)	N
# of res. parcels in SFHA or Sandy-affected	90.05 (394.61)	236.18 (611.70)	241.19 (622.68)	108.83 (117.16)	Y
Share of res. parcels in SFHA or Sandy-affected	0.06 (0.19)	0.16 (0.28)	0.17 (0.28)	0.14 (0.17)	Y*
# of res. parcels within expected SLR 6ft	96.78 (416.31)	251.48 (645.05)	257.93 (656.08)	87.48 (158.17)	Y
Share of res. parcels within expected SLR 6ft	0.07 (0.20)	0.17 (0.30)	0.17 (0.30)	0.13 (0.24)	Y*
Share of white population	0.67 (0.26)	0.73 (0.23)	0.73 (0.23)	0.71 (0.18)	N
Share of black population	0.15 (0.22)	0.12 (0.17)	0.12 (0.17)	0.13 (0.15)	Y*
Share of Hispanic population	0.19 (0.21)	0.17 (0.16)	0.17 (0.16)	0.22 (0.12)	Y
Share of family households	0.69 (0.12)	0.68 (0.12)	0.68 (0.12)	0.73 (0.09)	Y
Share of households in poverty	0.11 (0.10)	0.10 (0.09)	0.10 (0.09)	0.08 (0.07)	N
Share of foreign-born population	0.21 (0.16)	0.19 (0.15)	0.19 (0.15)	0.27 (0.12)	Y
Avg. crime index	84.6 (104.4)	84.8 (106.7)	86.1 (107.9)	52.4 (59.8)	N*
# of applicants receiving FEMA IHP assistance	20.44 (67.78)	42.90 (102.51)	43.34 (104.24)	31.60 (36.65)	Y*
Avg. amount paid by NFIP ('000$)	15.03 (51.75)	26.82 (51.80)	25.97 (51.80)	48.21 (47.82)	Y
# of HGMP-elevated homes	0.95 (4.19)	2.13 (6.27)	2.20 (6.37)	0.49 (1.76)	N*
Dist. closest beach recently nourished (km)	34.20 (19.51)	29.65 (21.46)	30.02 (21.56)	20.07 (16.39)	Y

Note: Standard Deviations in parentheses. Col. 1 contains summary statistics for all census tract in NJ. All census tracts that fall within municipalities authors defined as at high risk under the NJBAP criteria are shown in col. 2. Col. 3 displays data for census tracts deemed at high risk without any observed buyouts. Col. 4 includes census tracts deemed at high risk that received buyouts. Col. 5 displays if the observed differences in characteristics between col. 3 and col. 4 are statistically significant at 10 percent confidence level based on Wilcoxon rank sum test and t test. When the results of the two tests contradict (indicated as “*”), we based our decision of which result to report on the histogram of sample distributions.

Table 3. Estimation Results of Buyout Count Models with Different Specifications

	(1)	(2)	(3)
Model	Neg. binomial	Neg. binomial	Neg. binomial
Unit of observation	Municipality	Census tract	Census tract
Total revenues (TR) (million$)	0.032*	-0.104	-0.096
	(0.019)	(0.110)	(0.094)
Property tax as % of TR	1.948	-4.296**	-4.284*
	(6.919)	(1.786)	(2.336)
Avg. net assessed values (thousand$)	-0.005	-0.023***	-0.025***
	(0.004)	(0.004)	(0.006)
Avg. property taxes paid (thousand$)	-0.124	0.119***	0.122**
	(0.321)	(0.046)	(0.051)
Share of res. parcels	17.029	-7.836***	-7.962***
	(10.440)	(1.463)	(1.677)
Share of vacant parcels	61.191**	-6.891	-4.659
	(24.231)	(6.374)	(6.587)
Share of owner-occupied parcels	-1.250	3.631	4.311
	(5.381)	(2.761)	(2.809)
Public goods exp. as % of TR	-1.624	-2.106	-2.271
	(2.018)	(1.292)	(1.411)
Share of res. parcels in SFHA	-11.959	14.603***	22.777***
	(8.628)	(5.294)	(7.373)
Share of res. parcels in 6’ SLR	7.719	-4.518	-9.835*
	(7.723)	(3.922)	(5.121)
Dist. nearest nourished beach (km)	-0.246**	-0.263***	-0.250**
	(0.124)	(0.085)	(0.106)
Long-term debt as % of TR	1.219	1.177**	1.437**
	(0.752)	(0.518)	(0.583)
# of households approved for IHP	-0.007		0.004
	(0.005)		(0.019)
# of elevated homes	0.135		-0.664**
	(0.106)		(0.288)
Number of applications at municipality level	0.097**		
	(0.043)		
At least one applicant at municipality level		2.158**	2.321***
		(0.926)	(0.845)
Observations	506	1,936	1,936
Demographics included	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Standard errors clustering	Municipality	Municipality	Municipality
Log-likelihood	-91.798	-188.8	-186.58
BIC	326.73	552.18	561.17

Note: ∗ $p < 0.10$, ∗∗ $p < 0.05$, ∗∗∗ $p < 0.01$

Table 4. Hurdle Model and Heckman Model Estimation Results

	Hurdle Model		Heckman Model	
	Support	Buyout count	Support	Buyout count
Total Revenue (TR) (millions$)	-0.098 (0.104)		-0.141*** (0.029)	
Property tax as % of total revenue (TR)	-3.614*** (1.376)		-1.434*** (0.388)	
Avg. net assessed values (thousand$)	-0.007* (0.004)	0.001 (0.003)	-0.002** (0.001)	0.027*** (0.012)
Avg. property taxes paid (thousand$)	0.072*** (0.027)	-0.002 (0.017)	0.019** (0.007)	-0.171 (0.109)
Share of residential parcels	-3.408*** (1.161)	-2.372*** (0.916)	0.670* (0.381)	-15.506*** (4.591)
Share of vacant parcels	0.616 (4.960)	-5.102 (4.042)	-0.388 (0.977)	20.601 (12.956)
Share of owner-occupied parcels	2.849 (1.982)	1.986 (1.972)	-0.775* (0.418)	7.234 (5.706)
Public goods exp. as % of TR	-3.610** (1.684)		-0.648*** (0.142)	
Share of res. parcels in SFHA	4.587* (2.522)	8.525** (3.312)	-0.707 (0.708)	20.825* (12.081)
Share of res. parcels in 6-feet SLR	-2.598 (2.533)	-0.338 (2.967)	-2.056*** (0.700)	30.363** (12.752)
Dist. nearest nourished beach (km)	-0.036* (0.020)		-0.048*** (0.005)	
Long-term debt as % of TR	-0.104 (0.600)		0.073** (0.033)	
# of households approved for IHP	0.004 (0.005)	0.009** (0.004)	-0.014*** (0.004)	0.140*** (0.044)
# of elevated homes	-0.065 (0.134)	-0.339*** (0.118)	0.082*** (0.031)	0.812* (0.446)
Number of applications at municipality level	0.019*** (0.003)		0.037*** (0.002)	
rho			-0.896*** (0.042)	
Observations	1,935		1,935	
Demographics included	Yes		Yes	
AIC	410.1		1855.7	

Note: Unit of observation is at the census tracts. The dependent variables in “Support” columns and “Buyout count” are a binary dummy = 1 if the municipality has buyouts and the number of buyouts in each census tract, respectively. ∗ $p < 0.10$, ∗∗ $p < 0.05$, ∗∗∗ $p < 0.01$

APPENDIX (For On-line Publication)

Barriers to Coastal Managed Retreat:
Evidence from New Jersey's Blue Acres Program

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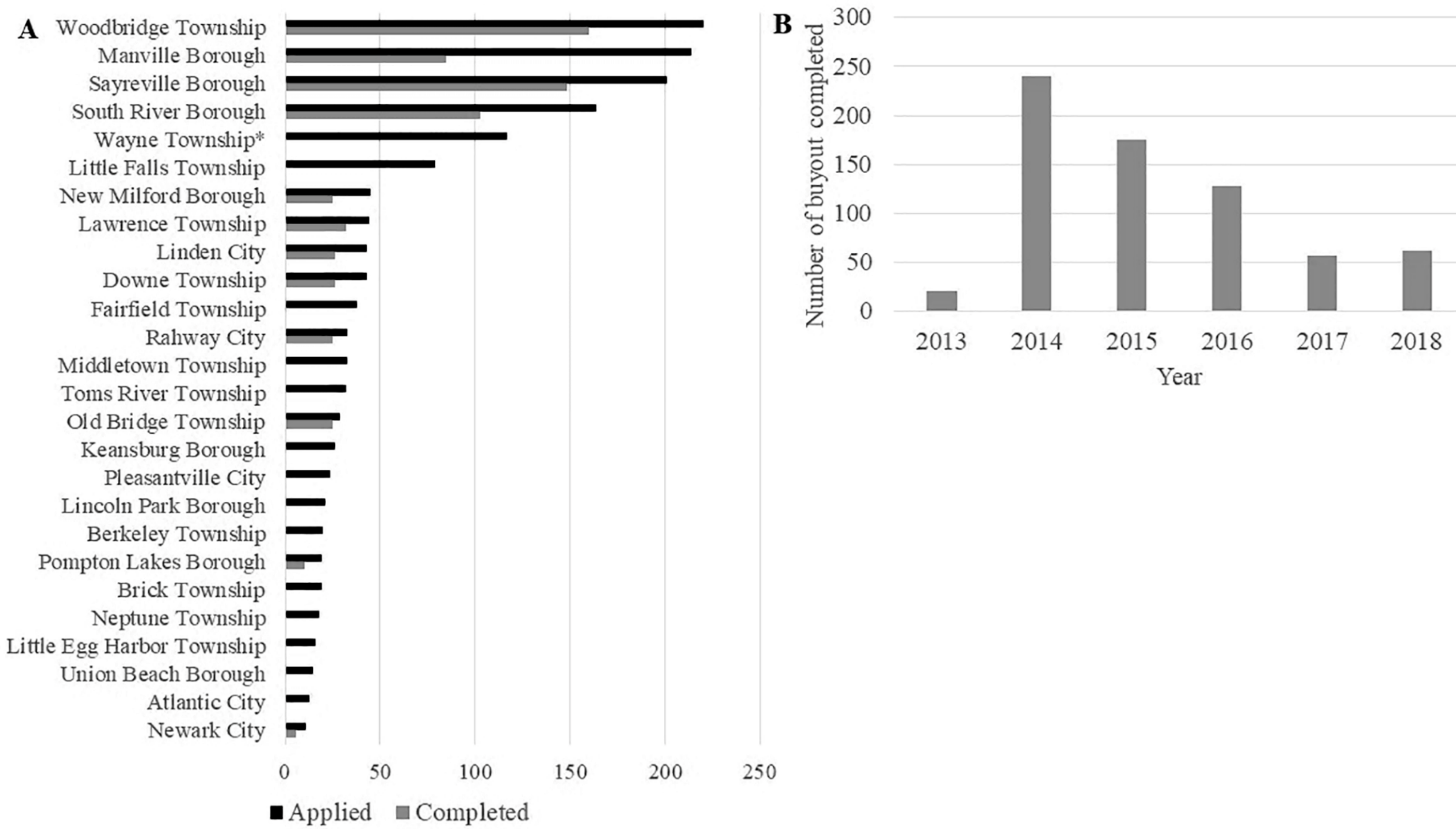
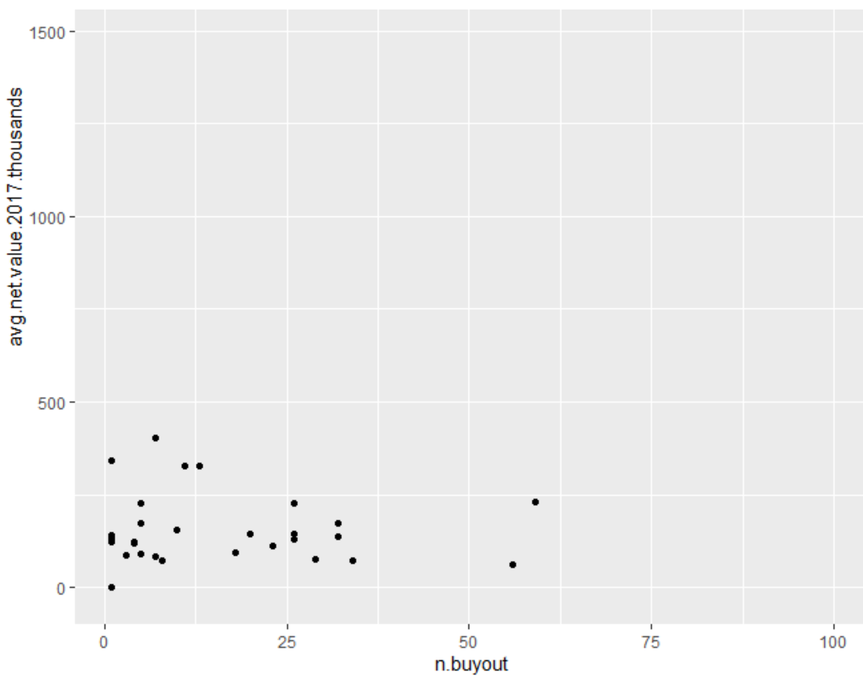


Figure S1. Property Acquisition through New Jersey Blue Acres Program 2013 – 2018

Note: Panel A shows the number of purchased properties in NJBAP program by municipality. The completed properties include properties that have completed the buyout process as of December 31, 2018. Panel B depicts the number of purchased properties in NJBAP by year. * Wayne Township used a private buyout process instead of NJBAP.

A



B

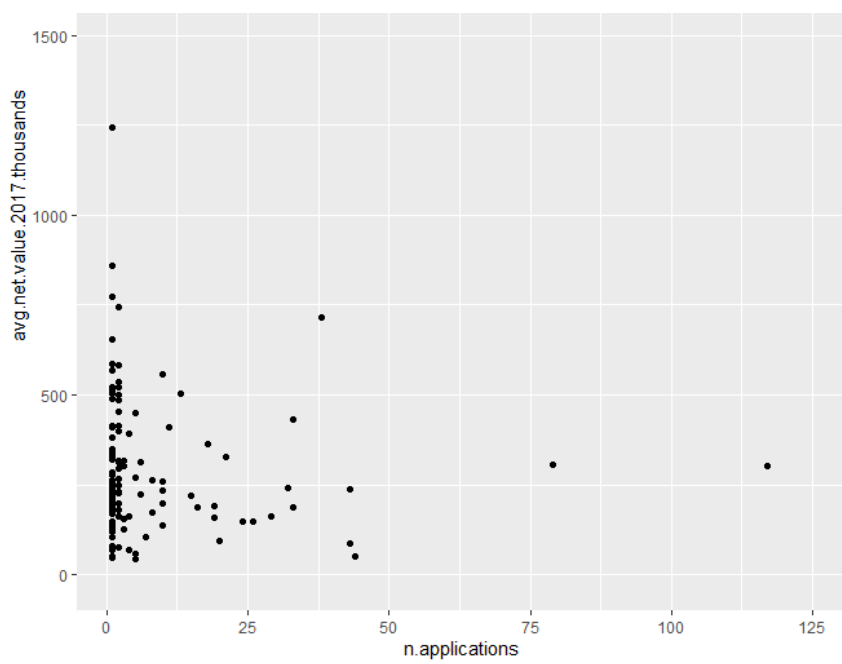


Figure S2. Buyout Counts and Applications by Municipality Average Assessed Property Values

Note: Panel A shows municipalities by buyout counts and average assessed property values. Panel B shows municipalities by application counts and average assessed property values.

Table S1. Summary Statistics for Municipalities by Application and Buyout Outcomes

	(1) No Applications (N = 431)	(2) Applications / No Buyouts (N = 119)	(3) Buyouts (N = 14)
Total revenues (TR) ('000 USD)	17,445 (24,122)	31,772 (65,382)	61,959 (100,263)
TR per HH ('000 USD)	12 (65)	5 (8)	4.99 (3.20)
Long-term debt share of TR	1.30 (7.57)	0.79 (0.67)	0.71 (0.42)
Property tax as share of TR	0.90 (0.14)	0.88 (0.14)	0.84 (0.19)
Public goods expenditure share of TR	0.55 (2.33)	0.49 (0.42)	0.41 (0.19)
Avg residential net assessed value ('000 USD)	402 (515)	300 (192)	177 (135)
Intergov revenues-federal ('000 USD)	513.02 (2,320)	2,180 (9,146)	2,004 (3,880)
Intergov revenues-federal per HH ('000 USD)	0.13 (0.59)	0.23 (0.66)	0.13 (0.17)
Intergov revenues-local ('000 USD)	251 (1,125)	602 (1,950)	5,905 (21,481)
Intergov revenues-local per HH ('000 USD)	0.12 (0.48)	0.09 (0.22)	0.24 (0.80)
Total outstanding long-term debt ('000 USD)	15,051 (34,258)	26,813 (69,571)	58,161 (111,118)
Total outstanding long-term debt per HH ('000	7.60 (41.02)	4.02 (5.24)	3.86 (4.00)
Δ long-term debt 2012-17 ('000$)	-1,183 (19,123)	-5,717 (23,790)	-14,547 (50,835)
Δ total revenues 2012-17 ('000$)	1,862 (9,878)	6,611 (31,636)	-2,884 (25,224)
Δ property tax 2012-17 ('000$)	2,117 (9,523)	5,269 (27,358)	7,387 (10,702)
Δ property tax share of TR 2012-17	0.01 (0.09)	0.00 (0.08)	0.06 (0.10)
Δ debt share of TR 2012-17	0.18 (7.07)	-0.29 (0.64)	-0.07 (0.40)
Share of residential parcels	0.74 (0.16)	0.71 (0.18)	0.69 (0.23)
Share of vacant parcels	0.04 (0.04)	0.06 (0.05)	0.06 (0.09)
Share of res. parcels in SFHA or Sandy-affected	0.07 (0.20)	0.19 (0.29)	0.07 (0.13)
Share of res. parcels expected SLR 6ft	0.07 (0.27)	0.27 (0.59)	0.09 (0.25)
Share of tracts facing the Atlantic coast	0.06 (0.23)	0.18 (0.39)	0.00 (0.00)
Dist. to the closest beach recently nourished (km)	40.71 (20.77)	27.96 (24.62)	22.86 (17.05)
# of applicants receiving FEMA IHP assistance	23 (71)	248 (535)	147 (144)
# of HGMP-elevated homes	0.90 (5.83)	12.49 (30.09)	2.40 (7.18)
Avg. FEMA inspected damage ('000 USD)	1.41 (3.37)	4.85 (10.02)	2.94 (4.77)
Total damage recorded by FEMA ('000 USD)	330 (1,320)	4,793 (11,766)	2,064 (2,513)
Total FEMA IHP assistance ('000 USD)	159 (644)	2,089 (5,114)	1,205 (1,523)
Total amount paid by NFIP ('000 USD)	2,728 (14,922)	25,655 (64,916)	4,615 (5,070)
Average amount paid by NFIP ('000 USD)	11 (30)	22 (28)	25 (25)
Share of owner-occupied housing units	0.66 (0.19)	0.62 (0.19)	0.60 (0.15)
Median household income ('000 USD)	95 (34)	80 (25)	77 (21)
Share of white residents	0.79 (0.17)	0.79 (0.17)	0.70 (0.19)
Share of Black residents	0.08 (0.12)	0.09 (0.11)	0.13 (0.15)
Share of Hispanic residents	0.13 (0.14)	0.13 (0.13)	0.19 (0.09)
Share of family households	0.71 (0.09)	0.70 (0.08)	0.71 (0.06)
Share of households in poverty	0.08 (0.06)	0.09 (0.06)	0.10 (0.05)
Average crime index	49 (54)	55 (65)	62 (74)
Share of parcels flooded in cluster	0.24 (0.43)	0.66 (0.48)	0.93 (0.27)

Table S2. Full Estimation Results of Buyout Count Models with Different Specifications

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model	Poisson	Neg. binomial	Neg. binomial	Poisson	Neg. binomial	Neg. binomial	Neg. binomial
Unit of observation	Municipality	Municipality	Municipality	Census tract	Census tract	Census tract	Census tract
Total revenues (TR) (millions$)	0.006	0.030***	0.032*	-0.298**	-0.141	-0.096	-0.104
	(0.004)	(0.008)	(0.019)	(0.145)	(0.093)	(0.094)	(0.110)
Property tax as % of TR	-1.412	4.563	1.948	-4.620***	-2.849*	-4.284*	-4.296**
	(1.239)	(6.356)	(6.919)	(1.582)	(1.618)	(2.336)	(1.786)
Avg. net assessed values (thousand$)	-0.003	-0.009**	-0.005	-0.030**	-0.018***	-0.025***	-0.023***
	(0.004)	(0.004)	(0.004)	(0.014)	(0.006)	(0.006)	(0.004)
Avg. property taxes paid (thousand$)	-0.013	0.244	-0.124	-0.031	0.067**	0.122**	0.119***
	(0.118)	(0.160)	(0.321)	(0.035)	(0.031)	(0.051)	(0.046)
Share of res. parcels	-0.351	20.337***	17.029	-3.386**	-6.908***	-7.962***	-7.836***
	(1.230)	(7.765)	(10.440)	(1.392)	(1.821)	(1.677)	(1.463)
Share of vacant parcels	19.733***	65.799***	61.191**	-2.447	-4.304	-4.659	-6.891
	(6.993)	(24.806)	(24.231)	(5.102)	(6.843)	(6.587)	(6.374)
Share of owner-occupied parcels	1.259	-2.385	-1.250	5.402***	7.750**	4.311	3.631
	(2.760)	(3.003)	(5.381)	(1.485)	(3.147)	(2.809)	(2.761)
Public goods exp. as % of TR	-0.248	-2.174**	-1.624	2.863	-2.772**	-2.271	-2.106
	(0.815)	(0.973)	(2.018)	(1.892)	(1.253)	(1.411)	(1.292)
Share of res. parcels in SFHA	0.354	-12.245	-11.959	16.749**	22.111***	22.777***	14.603***
	(8.156)	(8.202)	(8.628)	(7.543)	(5.683)	(7.373)	(5.294)
Share of res. parcels in 6' SLR	2.304	7.768	7.719	-5.964	-8.066*	-9.835*	-4.518
	(3.926)	(6.945)	(7.723)	(4.263)	(4.439)	(5.121)	(3.922)
Dist. nearest nourished beach (km)	-0.013	-0.216***	-0.246**	-0.045	-0.180**	-0.250**	-0.263***
	(0.065)	(0.076)	(0.124)	(0.068)	(0.091)	(0.106)	(0.085)
Long-term debt as % of TR	0.378	1.493**	1.219	-0.499	1.109*	1.437**	1.177**
	(0.333)	(0.613)	(0.752)	(0.544)	(0.618)	(0.583)	(0.518)
# of households approved for IHP	0.002	-0.009*	-0.007	0.030**	0.011	0.004	
	(0.004)	(0.005)	(0.005)	(0.012)	(0.017)	(0.019)	
# of elevated homes	0.044	0.174	0.135	-0.293**	-0.537***	-0.664**	
	(0.058)	(0.121)	(0.106)	(0.138)	(0.199)	(0.288)	

Table S2. Full Estimation Results of Buyout Count Models with Different Specifications (continued)

Share of Black residents			-4.057 (7.455)			-8.712*** (2.810)	-8.127*** (3.127)
Share of Hispanic residents			-4.209 (7.796)			-0.549 (1.957)	0.323 (2.174)
Avg. crime index			-0.012 (0.027)			-0.013*** (0.005)	-0.014*** (0.004)
Share of pop. with children < 18			-9.870 (16.789)			7.886* (4.647)	8.015 (5.227)
Share of pop. > 65 years old			1.057 (13.727)			-6.174 (10.128)	-4.066 (8.929)
Share of foreign-born population			18.290* (10.613)			-7.819 (4.754)	-7.093 (4.441)
Number of applications at municipality level	0.023** (0.009)	0.110*** (0.037)	0.097** (0.043)				
At least one applicant at municipality level				6.209* (3.244)	1.875** (0.795)	2.321*** (0.845)	2.158** (0.926)
Observations	506	506	506	1,936	1,936	1,936	1,936
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Standard errors clustering	Municipality	Municipality	Municipality	Municipality	Municipality	Municipality	Municipality
Log-likelihood	-241.7	-92.593	-91.798	-573.98	-191.03	-186.58	-188.8
BIC	707.56	297.65	326.73	1,428.00	529.79	561.17	552.18

Notes: $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$

Table S3. Full Hurdle Model Estimation Results

	(1)		(2)		(3)	
	Support	Buyout count	Support	Buyout count	Support	Buyout count
Total Revenue (TR) (millions$)	-0.079 (0.089)		-0.091 (0.099)		-0.098 (0.104)	
Property tax as % of total revenue (TR)	-3.307*** (1.148)		-3.759*** (1.363)		-3.614*** (1.376)	
Avg. net assessed values (thousand$)	-0.007** (0.003)	-0.004 (0.003)	-0.007* (0.004)	0.001 (0.003)	-0.007* (0.004)	0.001 (0.003)
Avg. property taxes paid (thousand$)	0.061** (0.025)	-0.026 (0.020)	0.072*** (0.028)	0.002 (0.021)	0.072*** (0.027)	-0.002 (0.017)
Share of residential parcels	-2.931** (1.141)	-1.064 (1.221)	-3.426*** (1.167)	-2.709** (1.156)	-3.408*** (1.161)	-2.372*** (0.916)
Share of vacant parcels	-0.212 (3.901)	4.778 (4.290)	0.350 (4.636)	-8.158 (5.241)	0.616 (4.960)	-5.102 (4.042)
Share of owner-occupied parcels	1.326 (1.381)	1.538 (1.440)	2.794 (1.968)	1.144 (2.384)	2.849 (1.982)	1.986 (1.972)
Public goods exp. as % of TR	-3.169** (1.450)		-3.533** (1.600)		-3.610** (1.684)	
Share of res. parcels in SFHA	3.253* (1.823)	10.232** (4.678)	4.856* (2.483)	2.258 (3.386)	4.587* (2.522)	8.525** (3.312)
Share of res. parcels in 6-feet SLR	-2.037 (1.999)	-4.776 (3.818)	-2.527 (2.526)	3.913 (3.745)	-2.598 (2.533)	-0.338 (2.967)
Dist. nearest nourished beach (km)	-0.034* (0.020)		-0.038* (0.020)		-0.036* (0.020)	
Long-term debt as % of TR	-0.451 (0.624)		-0.081 (0.597)		-0.104 (0.600)	
# of households approved for IHP					0.004 (0.005)	0.008** (0.004)
# of elevated homes					-0.065 (0.134)	-0.339*** (0.118)
Number of applications at municipality level	0.019*** (0.003)		0.019*** (0.003)		0.019*** (0.003)	
Share of Black residents			2.263 (1.984)	-4.796** (2.118)	2.263 (1.998)	-4.628** (1.902)
Share of Hispanic residents			3.392 (2.078)	8.243*** (3.017)	3.373 (2.085)	8.012*** (2.498)
Avg. crime index			-0.007 (0.005)	-0.014*** (0.005)	-0.007 (0.005)	-0.012*** (0.004)
Share of population with children < 18			1.419 (6.451)	-2.293 (5.352)	1.433 (6.436)	-4.910 (4.526)
Share of population > 65			-3.349 (7.125)	-10.589 (7.764)	-3.607 (7.144)	-13.810** (6.855)
Share of foreign-born population			-1.486 (1.655)	-1.575 (3.069)	-1.445 (1.676)	-2.963 (2.509)
Observations	1,936		1,936		1,936	

Table S3. Full Hurdle Model Estimation Results (continued)

Demographics included	No	Yes	Yes
AIC	405.0	411.9	410.1
BIC	533.1	606.8	627.3

Notes: Unit of observation is at the census tracts. Specification (1) only includes balanced-budget variables. Specification (2) adds demographic variables. Specification (3) further adds government transfer variables. The dependent variables in "Support" columns and "Buyout count" are a binary dummy = 1 if the municipality has buyouts and the number of buyouts in each census tract, respectively. $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.0$

Table S4. Full Heckman Selection Model Estimation Results.

	(1)		(2)		(3)	
	Support	Buyout count	Support	Buyout count	Support	Buyout count
Total revenues (TR) (millions$)	-0.130***		-0.148***		-0.141***	
	(0.025)		(0.029)		(0.029)	
Property tax as % of total revenue (TR)	-1.396***		-1.285***		-1.434***	
	(0.291)		(0.383)		(0.388)	
Avg. net assessed values (thousand$)	-0.003***	0.032***	-0.002***	0.022**	-0.002**	0.027***
	(0.001)	(0.009)	(0.001)	(0.010)	(0.001)	(0.012)
Avg. property taxes paid (thousand$)	0.014**	-0.152	0.019***	-0.175	0.019**	-0.171
	(0.006)	(0.102)	(0.007)	(0.112)	(0.007)	(0.109)
Share of residential parcels	0.497	-11.881***	0.652*	-15.825***	0.670*	-15.506***
	(0.317)	(4.406)	(0.370)	(4.745)	(0.381)	(4.591)
Share of vacant parcels	1.300	1.769	-0.577	22.369*	-0.388	20.601
	(0.797)	(11.312)	(0.979)	(13.420)	(0.977)	(12.956)
Share of owner-occupied parcels	-1.912***	16.445***	-0.755*	7.036	-0.775*	7.234
	(0.289)	(3.638)	(0.412)	(5.864)	(0.418)	(5.706)
Public goods exp. as % of TR	-0.324***		-0.639***		-0.648***	
	(0.085)		(0.140)		(0.142)	
Share of res. parcels in SFHA	-0.031	20.001*	-0.668	31.485**	-0.707	20.825*
	(0.652)	(11.643)	(0.682)	(12.396)	(0.708)	(12.081)
Share of res. parcels in 6-feet SLR	-2.776***	33.143***	-2.391***	25.341*	-2.056***	30.363**
	(0.728)	(12.495)	(0.711)	(13.280)	(0.700)	(12.752)
Dist. nearest nourished beach (km)	-0.028***		-0.035***		-0.048***	
	(0.004)		(0.004)		(0.005)	
Long-term debt as % of TR	0.044		0.066**		0.073**	
	(0.032)		(0.030)		(0.033)	
# of households approved for IHP					-0.014***	0.140***
					(0.004)	(0.044)
# of elevated homes					0.082***	0.812*
					(0.031)	(0.446)
Number of applications at municipality level	0.034***		0.035***		0.037***	
	(0.002)		(0.002)		(0.002)	
Share of Black residents			0.872**	-1.245	0.841**	0.833
			(0.361)	(5.840)	(0.372)	(5.721)
Share of Hispanic residents			0.060	9.735*	0.075	12.571**
			(0.392)	(5.900)	(0.397)	(5.726)
Avg. crime index			0.004***	-0.041***	0.005***	-0.036***
			(0.001)	(0.010)	(0.001)	(0.009)
Share of population with children < 18			-1.319	6.147	-1.528	13.240
			(1.200)	(18.019)	(1.214)	(17.586)
Share of population > 65			-1.101	22.599	-1.215	32.835
			(1.221)	(21.487)	(1.249)	(20.784)
Share of foreign-born population			0.036	-4.134	-0.164	-0.653
			(0.388)	(8.823)	(0.411)	(8.563)

Table S4. Full Heckman Selection Model Estimation Results (continued)

rho	-0.916*** (0.032)	-0.857*** (0.053)	-0.896*** (0.042)
Observations	1,936	1,935	1,935
Demographics included	No	Yes	Yes
AIC	1947.2	1888.8	1855.7
Log-likelihood	-949.624	-908.411	-887.873

Notes: Specification (1) only includes balanced-budget variables. Specification (2) adds demographic variables. Specification (3) further adds government transfer variables.
∗ $p < 0.10$, ∗∗ $p < 0.05$, ∗∗∗ $p < 0.01$