Estimation of an Equilibrium Model with Externalities: Combining the Strengths of Structural Models and Quasi-Experiments*

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Abstract

We study the optimal design of subsidies in an equilibrium setting, where the decisions of individual recipients impose externalities on one another. We apply the model to the case of post-Katrina rebuilding in New Orleans under the Louisiana Road Home rebuilding grant program (RH). We estimate the structural model via indirect inference, exploiting a discontinuity in the formula for determining the size of grants, which helps isolate the causal effect of neighbors’ rebuilding on one’s own rebuilding choices. We find that the additional rebuilding induced by RH generated positive externalities equivalent to $4,950 to each inframarginal household whose rebuilding choice was not affected by the program. Counterfactual policy experiments find that optimal subsidy policies bias grant offers against relocation, with an inverse-U-shaped relationship between the degree of bias and the severity of damages from the disaster.

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1 Introduction

Individuals’ choices are sometimes inevitably and endogenously inter-related due to spillover effects from one’s choices onto others’ payoffs. These spillovers are often not accounted for when individuals make their decisions, which may lead to inefficient equilibrium outcomes and hence leave space for policy interventions.\(^1\) Effective policy designs require the capability of predicting and comparing the impacts of alternative counterfactual policies, which in turn relies on two essential pieces of information. The first is an understanding of the nature of the spillover effects, which can be difficult to identify.\(^2\) The second is an understanding of both the factors underlying individuals’ decisions and the way private choices spillover onto others’ choices in equilibrium.\(^3\) In this paper, we develop a unified framework to obtain both pieces of information.

To place our framework in a concrete setting, we develop an equilibrium model of neighbors’ post-disaster rebuilding choices with amenity spillovers. Households have private preferences for consumption and for residing in their home. They also derive utility from a neighborhood amenity that depends on the fraction of neighbors who rebuild, an externality that is not internalized by individual households. In each period, households who have not yet rebuilt or sold their houses have the option to rebuild, sell or wait. Households’ decisions are inter-related because of amenity spillovers, the shape and scale of which is embedded in the structure of the model. An equilibrium requires that individuals’ decisions be best responses to each other.

We apply our model to the rebuilding of neighborhoods affected by Hurricane Katrina. We estimate our model using administrative microdata from the Louisiana Road Home program (RH), which offered rebuilding grant packages and less generous relocation grant packages to all Katrina-affected homeowners in the state with uninsured losses. The RH grant formula yielded significantly larger grant offers when an index measuring home damages fell above a particular threshold. As a result, otherwise similar households with index values just above/below this threshold faced very different financial incentives to rebuild. We exploit this program artifact as a source of identification of our structural equilibrium model.

The estimated model reveals important policy implications arising from amenity spillovers.

\(^1\)For instance, negative spillovers from home foreclosures are a commonly cited motivation for subsidized mortgage modifications (Cambell, Giglio, Pathak, 2010). Arguments against rent controls often cite the possibility that undermaintained properties reduce the value of nearby non-controlled properties (Autor, Palmer, and Pathak, 2012).

\(^2\)Manski (1993) raises the reflection problem. Brock and Durlauf (2007) show that point identification of social interactions can fail even when there is no reflection problem in settings where important group-level variables are not observed by the researcher.

\(^3\)In an ideal world, carefully designed random experiments could help conquer these obstacles, although with substantial cost.
RH’s full equilibrium impact on the city-wide rebuilding rate, including “feedback” effects from positive amenity spillovers, was 27% larger than the impact generated by the program’s financial incentives alone (holding amenities fixed). Like many other government disaster relief packages, the RH program’s structure provided a higher financial incentive to rebuild than to relocate. Although the conditional nature of the program created excess burden by distorting privately optimal resettlement choices, the spillover effects were strong enough such that the net average household welfare was $2,177 higher under RH than it would have been had households been offered the same grant regardless of whether they chose to rebuild or to relocate.

Our framework is well-suited for exploring a wide range of policy interventions with various goals and/or constraints. For illustration, we examine the possibility of further improving welfare by studying a particular group of conditional grant policies, which offer a fraction \((1 - \rho)\) of the RH rebuilding grant to households if they choose to relocate. We search for the optimal \(\rho\)’s given different constraints. Compared to the case under the unconditional grant policy, net average household welfare would improve by $2,638 if \(\rho\)’s are restricted to be the same for all households, by $3,613 if \(\rho\)’s can differ by flooding severity, and by over $6,000 if \(\rho\)’s can be block-specific. The relationship is inversed-U-shaped between the optimal penalties against relocation \((\rho)\) and the severity of damages from the disaster, with greater biases against relocation for areas with moderate damages.

Although our empirical application focuses on a special event, our equilibrium modeling framework can be applied/extended to other cases where individual decisions inter-relate due to spillover effects. Our findings highlight the fact that, when externalities potentially exist, accounting for equilibrium interactions among individuals and quantifying the externality is essential for the design of policies. To shed light on policy designs with relatively less restrictive modeling assumptions for identification, our paper combines the strengths of two strands of the literature on spillover effects, one relying on quasi-experiments and the other on structural models.

Consistent with our estimates, reduced-form analyses in the first strand of literature have found evidence that policies stimulating investment in housing boost the value of nearby homes not directly affected by the policies (Autor, Palmer, and Pathak 2012; Rossi-Hansberg, Sarte, and Owens 2010), and that negative spillover effects of foreclosures are larger for more proximate homes (Campbell, Giglio, and Pathak 2011; Harding, Rosenblatt, and Yao 2009). In the second strand of literature, de Paula (2009) is the closest to our work.\(^4\) He studies other recent examples of equilibrium model-based approaches to studying housing and/or location choices include; Epple and Sieg (1999); Epple, Romer, and Sieg (2001); Ioannides (2003); Bayer, McMillan, and Reuben (2005); Bayer, Ferreira, and McMillan (2007); Bayer and Timmins (2007); and Ioannides and Zabel (2008).

\(^4\)Other recent examples of equilibrium model-based approaches to studying housing and/or location choices include; Epple and Sieg (1999); Epple, Romer, and Sieg (2001); Ioannides (2003); Bayer, McMillan, and Reuben (2005); Bayer, Ferreira, and McMillan (2007); Bayer and Timmins (2007); and Ioannides and Zabel (2008).
inference in a continuous time model where an agent’s payoff to quit an activity depends on the participation of other players. Ours is a discrete time model where neighbors’ choices of the timing of rebuilding are inter-related. Our paper embeds variation from a quasi-experiment in our structural model to estimate the shape and strength of social spillovers.\textsuperscript{5}

Although experimentally-generated variation in incentives is not always available, different and more general identification strategies than the one used in this paper are available, which typically require more structure on, for example, the selection into groups/neighborhoods.\textsuperscript{6}

For example, Brock and Durlauf (2006) and Brock and Durlauf (2007) provide methods for identifying social interactions in discrete choice models with endogenous group formation. Brock and Durlauf (2007) demonstrate partial identification of social interactions with unobserved neighborhood-level covariates. Bayer and Timmins (2007) propose an instrument for peers’ behavior that is based on exogenous location characteristics and motivated by a formal location choice model to identify spillovers.

Our paper is also related to the literature studying the post-Hurricane-Katrina locations, labor market outcomes, and wellbeing of displaced New Orleans residents.\textsuperscript{7} Most closely to our paper, Gregory (2014) estimates a structural individual decision model of New Orleans homeowners’ resettlement choices. Gregory (2014) uses the estimated model to study the trade-off of post-disaster bailouts between their short run insurance benefits and the long run efficiency losses caused by expected future bailouts distorting households’ location choices (moral hazards). Instead of treating each household in isolation, our paper emphasizes the possible spillover effects from individual households’ choices and the inter-related nature of households’ choices in an equilibrium context. We study the optimal design of conditional subsidies that internalize spillover effects and improve household welfare in equilibrium.

The rest of the paper is organized as follows: Section 2 provides additional policy background. Section 3 describes the structural equilibrium model. Section 4 describes our dataset. Section 5 explains our estimation. Section 6 presents the estimation results. Section 7 presents our counterfactual experiments, and section 8 concludes. The appendix contains additional details.

\textsuperscript{5}Galiani, Murphy, and Pantano (2012) use the experimentally randomized variation in neighborhood-specific financial incentives from the Moving to Opportunity (MTO) demonstration to identify the structural parameters of an individual neighborhood choice model (without social interactions).

\textsuperscript{6}See Blume, Brock, Durlauf, and Ioannides (2010) for a comprehensive review of the literature on the identification of social interaction effects.

\textsuperscript{7}For example, Groen and Polivka, 2010; Zissimopolous and Karoly, 2010; Vigdor, 2007 and 2008; Paxson and Rouse, 2008; and Elliott and Pais, 2006.
2 Background Information

Hurricane Katrina struck the U.S. Gulf Coast on August 29, 2005. In the days following the storm’s initial impact, the levees that protect New Orleans gave way in several places, allowing flood waters to cover roughly 80% of the city (McCarthy et al., 2006). The storm and subsequent flooding left two thirds of the city’s housing stock uninhabitable without extensive repairs, the costs of which significantly exceeded insurance payouts for many pre-Katrina homeowners in New Orleans. Among the nearly 460,000 displaced residents, many spent a considerable amount of time away from the city or never returned.

In the months following Hurricane Katrina, Congress approved supplemental relief block grants to the Katrina-affected states.\(^8\) Possible uses of these grants were hotly debated, with proposals ranging from mandated buyouts to universally subsidized reconstruction. The state of the Louisiana used its federal allocation to create the Louisiana Road Home program, which provided cash grants for rebuilding or relocating to pre-Katrina Louisiana homeowners with uninsured damages.\(^9\)

A participating household could accept its RH grant as a rebuilding grant or as a relocation grant. Subject to an upper limit of $150,000, both grant types provided compensation equal to the “value of home damages” minus the value of any insurance payouts already received. As described in detail later, the RH grant formula yielded significantly larger grant offers when an index measuring home damages fell above a particular threshold. As a result, grant values were substantially different for otherwise similar households with index values just above/below this threshold. We exploit this program artifact as a source of identification of our structural equilibrium model.

There were several important differences between rebuilding and relocation grants. While both provided the same cash payout,\(^10\) relocation grant recipients were required to turn

\(^8\)Congress has regularly provided large Community Development Block Grants to local and state governments to assist with disaster recovery. Localities typically have considerable discretion over the use of these grants.

\(^9\)Other policies targeted to the Gulf Coast in the aftermath of Hurricane Katrina included Federal Emergency Management Agency (FEMA) small assistance grants in the hurricane’s immediate aftermath and Gulf Opportunity Zone subsidies to firms for capital reinvestments and the hiring and retention of displaced workers. The program other than RH that most directly impacted homeowners’ ability to rebuild was the Small Business Administration (SBA) Disaster Loan program, which provided loans to homeowners with uninsured damages who met certain credit standards. The SBA Disaster Loan program is a standing program that, despite being federally subsidized, has non-trivial credit standards, and the program rejected a large majority of applicants from the Gulf Coast in the aftermath of Katrina (Eaton and Nixon, 2005). For that reason, we allow for the possibility of credit constraints in our equilibrium model.

\(^10\)The cash grants for relocating and for rebuilding were the same except for one particular circumstance. All RH grants were initially capped at the pre-Katrina value of a household’s home. For households classified as “low or moderate income,” this cap was waved for rebuilding grants (in response to the argument that the provision had disparate impacts by race, because identical homes had different market values in
their properties over to a state land trust. For households with partial home damages, this stipulation introduced a sizable opportunity cost to relocating. On the other hand, rebuilding grant recipients were only required to sign covenant agreements to use their grants for rebuilding and to not sell their homes for at least three years. We provide additional details in Section 4.2 on the incentive effects of these program rules and differences in these incentives on either side of the grant formula discontinuity.

Grant recipients often experienced lengthy delays between initiating their grant applications and receiving a grant. RH was announced in February, 2006, but the median grant payment date occurred after Katrina’s second anniversary in 2007. Our equilibrium model captures the timing of the program’s rollout. Despite the program’s slow rollout, RH had disbursed nearly ten billion dollars to Louisiana homeowners by Katrina’s fifth anniversary.

3 Model

Displaced households (homeowners) make dynamic decisions about moving back to (and rebuilding) their pre-Katrina homes.\footnote{Moving back and rebuilding are defined as one indivisible action.} In every period, a household that has not moved back or sold its property can choose to 1) move back and rebuild, or 2) sell the property, or 3) wait until the next period. Each household’s decision potentially influences the block’s attractiveness, a spillover effect that is not internalized by individual households. The model incorporates the following factors that influence a household’s net payoff from rebuilding: (i) the cost of home repairs relative to other non-repair options, (ii) household’s labor market opportunities in and out of New Orleans, (iii) the strength of the household’s idiosyncratic attachment to the neighborhood, (iv) the exogenous state of the neighborhood (e.g., flood damages, infrastructure repairs and unobserved amenities), and (v) the influence of neighbors’ rebuilding choices on the attractiveness of the neighborhood.

\footnote{Moving back and rebuilding are defined as one indivisible action.}
3.1 Primitives

There are $J$ communities/blocks; and each block is the setting of an equilibrium.\textsuperscript{12} There are $I$ households living in different communities. Let $j(i)$ be the block where household $i$ owns its home, and $I_j$ be the set of households living in $j$. Hurricane Katrina occurs at time $t = 0$. Each household lives forever but has the option to rebuild each period only from 1 to $T$, where each period is one year.\textsuperscript{13} Households differ in their housing-related costs, labor market opportunities, levels of attachment to their community and accesses to credit. All information is public among neighbors but is only partially observed by the researcher.\textsuperscript{14}

3.1.1 Monetary Incentives

Housing-Related Costs Several housing-related costs and prices influence the financial consequences of each of the three options: 1) $i$’s remaining mortgage balance when Katrina occurred ($M_i \geq 0$); 2) the cost/value of the pre-Katrina physical structure of $i$’s house ($p_{s_i}^i$) (superscript $s$ for structure); 3) the cost of repairing/restoring the house from it’s damaged state ($k_i \leq p_{s_i}^i$); 4) the (endogenous) market value of the property (the damaged house and the land) if sold privately $p_i$, 5) the value of insurance payments received ($\text{ins}_i \leq k_i$); and 6) the additional incentives created by RH.

If household $i$ has yet to rebuild entering period $t$, the household may return and reside on the block in period $t$ by paying a one-time repair cost $k_i$ at the beginning of period $t$, i.e., within a year.\textsuperscript{15} Households who rebuild are reimbursed for uninsured damages by a RH (option 1) grant $G_{1i} = \min(\$150,000, k_i - \text{ins}_i)$. Reflecting RH’s slow rollout, grants are dispersed at the start of $t = 3$ if repairs occurred earlier and are dispersed at the time repairs occur otherwise.

\textsuperscript{12} We choose to focus on the equilibrium within each block in order to achieve a more detailed understanding of interactions and spillovers among neighbors. The choice to focus on blocks (specifically Census blocks) is data driven. See section 4.2.2 for details. An alternative modeling framework would treat a larger unit, e.g., the whole region, as one economy. Relative to our framework, the second framework may provide a broader view, but most likely at the cost of abstracting from some of the micro features we consider in order to remain tractable. Our goal in this paper is to form a solid understanding at a more micro level, which will serve as the basis for the next step, i.e., to embed our model into a more general equilibrium framework, which we leave as an extension for future work.

\textsuperscript{13} Empirically, we set $T = 5$.

\textsuperscript{14} Given that households in our model are neighbors, we have assumed a complete information structure. The main predictions from our model would still hold if one assumes incomplete information among neighbors. Regardless of the model’s information structure, however, it is reasonable to allow for and hence important to account for factors that are common knowledge to the households but are unobservable to the researcher.

\textsuperscript{15} For simplicity, we assume that rebuilding occurs during the same period (year) that the rebuilding cost is paid. This assumption should be realistic in the vast majority of cases, as 92% of residential construction starts are completed within one year, and the median time to completion is under six months (Census Survey of Construction, 2005-2010).
For each period that it resides away from its pre-Katrina block, a household rents accommodation comparable to its pre-Katrina home at a cost of \( rent_i = \delta \times p_{si} \), where \( \delta \) is the user cost of housing. The household can sell its property either through RH (option 2) for a price \( G_{2,i} \) or privately for a price \( p_i \). The private sales price, as we specify later, depends on the replacement cost of the structure \( (p_{si}) \), its damage \( (k_i) \), neighborhood characteristics, and the neighborhood’s rebuilding rate \( \mu_j \).

**Labor Market Opportunities**  Household \( i \) faces different wages in New Orleans \( \{w^1_{it}\}_t \), and outside of New Orleans \( \{w^0_{it}\}_t \). The two vectors of wages differ across households, which is another source of variation that may lead to different choices across households.

### 3.1.2 Household Preferences

A household derives utility from consumption \( (c) \), neighborhood amenities, and an idiosyncratic taste for a place. The values of the last two components are normalized to zero for the outside option. The (relative) value of amenities in community \( j \) consists of an exogenous part \( a_j \) and an endogenous part that depends on the fraction \( (\mu_{jt}) \) of neighbors who have rebuilt.\(^{16}\) Households differ in their attachment to their community \( (\eta_i) \), which stands for their private non-pecuniary incentives to return home, assumed to follow an i.i.d. \( N \left( 0, \sigma^2_\eta \right) \).

Household \( i \)’s per-period utility payoffs are characterized by,

\[
v_{it}(\mu_{j(i),t};d_{it}) = \begin{cases} 
\ln(c_{it}) & \text{if } d_{it} < 1 \\
\ln(c_{it}) + a_{j(i)} + g(\mu_{j(i),t}) + \eta_i & \text{if } d_{it} = 1,
\end{cases}
\]

where \( d_{it} = 1 \) if household \( i \) has chosen to rebuild by period \( t \), \( d_{it} = -1 \) if \( i \) has sold its house by time \( t \), and \( d_{it} = 0 \) if neither is true.\(^{17}\) \( \mu_{j(i),t} \in [0, 1] \) is the fraction of neighbors who have rebuilt by time \( t \), and \( g(\mu) \) is a non-decreasing function governing the amenity spillovers.\(^{18}\)

**Remark 1** Notice that \( d_{it} \) represents one’s status at time \( t \); one’s action at time \( t \) is reflected by a change in \( d_{it} \) relative to \( d_{it-1} \). We assume that both selling and rebuilding are absorbing

\(^{16}\)Presumably spillover effects can operate via channels that are more general than the rebuilding rate or the fraction of agents who take relevant actions. For feasibility reasons, the literature has typically abstracted away from more general spillover effects. For example, in Bayer and Timmins (2005), the fraction of neighbors taking the relevant action enters individuals utility linearly. We make a weaker assumption by allowing household utility to be a much more flexible function of the rebuilding rate.

\(^{17}\)More rigorous notation would explicitly acknowledge the dependence of \( v(.) \) on the other variables – i.e. \( v(c, a, \mu, \eta, d) \). We use the notation \( v_{it}(\mu_{j(i),t};d_{it}) \) to save notation and highlight the roll of block-level rebuilding decisions \( \mu \) and individual rebuilding decisions \( d \).

\(^{18}\)A non-decreasing spillover function rules out the possibility of particularly strong “congestion” effects, which we view as reasonable in our framework as the number of residents is not allowed to exceed the pre-disaster equilibrium level.
states and hence the only feasible changes in $d_{it}$ over time are $0 \rightarrow 1$ or $0 \rightarrow -1$. Therefore, $d_{it} > d_{it-1}$ is equivalent to rebuilding in period $t$; and $d_{it} < d_{it-1}$ is equivalent to selling in period $t$.\footnote{In the data, less than 4\% of households repair their home and then sell the home later during the sample window.}

### 3.1.3 Intertemporal Budget Constraint/Financing Constraints

The household intertemporal budget constraint is given by,

$$
\begin{align*}
c_{it} &= 1(d_{it} = 1) \times w_i^1 + 1(d_{it} < 1) \times w_i^0 \quad \text{\{labor earnings\}} \\
&\quad - 1(d_{it} < 1) \times \text{rent}_i - 1(d_{it} > -1) \times \text{mortgage}_{it} \quad \text{\{flow housing costs\}} \\
&\quad - 1(d_{it} > d_{it-1}) \times k_i \\
&\quad + 1(d_{t3} = 1 \text{ and } t = 3) \times G_{1i} \quad \text{\{repair costs/reimbursements\}} \\
&\quad + 1(d_{it} > d_{it-1} \text{ and } t > 3) \times G_{1i} \\
&\quad + 1(d_{it} < d_{it-1}) \times \max(G_{2i}, p_i) \quad \text{\{home sale proceeds\}} \\
&\quad + A_{it} - A_{it+1}/R_t \quad \text{\{change in asset holding\}}.
\end{align*}
$$

The first line gives one’s labor income, depending on whether one lives in or out of New Orleans, where $1(\cdot)$ is the indicator function. The second line is the flow housing cost, which equals the rent cost if one lives outside of the city plus the mortgage payment if the household still owns its home. The next line is the one-time repair cost one incurs if one rebuilds in this period ($d_{it} > d_{it-1}$). The next two lines summarize the grant one gets for rebuilding, reflecting the fact that the RH grants were typically paid out more than two years after Katrina. The second last line represents the event of a household selling its property ($d_{it} < d_{it-1}$), in which case the household chooses the better option between selling to RH and selling privately and obtain $\max\{G_{2i}, p_i\}$. Finally, the household can also change its asset holding at interest rate $R_t$, with the restriction that,

$$
A_{it} \geq \begin{cases} 
0 & \text{if } \text{risk}_i < \rho^* \\
-\infty & \text{if } \text{risk}_i \geq \rho^*
\end{cases},
$$

\begin{align*}
&\text{In the data, less than 4\% of households repair their home and then sell the home later during the sample window.}
\end{align*}
where \( risk_i \) is household \( i \)'s Equifax credit risk score \( risk_i \), which affects its access to credit.\(^{20}\)

Households with risk scores above a threshold \( \rho^* \) may borrow to finance home repairs, and households with risk scores below \( \rho^* \) are ineligible for loans.\(^{21}\)

**Property Sales Price**  The price at which a household can sell its home privately \( p_i \) is endogenous and affected by the equilibrium neighborhood rebuilding status, such that

\[
\ln (p_i) = P\left(p_i^s, k_i, z_{j(i)}, \mu_{j(i),T}\right) + \epsilon_i.
\]

The function \( P(\cdot) \) captures the physical value and the amenity value of the house. The physical value depends on the house’s pre-Katrina physical structure cost \( p_i^s \) and its damage status captured by \( k_i \), the cost of the repairs needed to fully restore the structure. The amenity value depends both on exogenous observable block characteristics captured by the vector \( z_{j(i)} \), and on the *endogenous* block rebuilding rate \( \mu_{j(i),T} \). We use the final rebuilding rate \( \mu_{j(i),T} \) as a determinant of the price to capture the idea that house buyers are forward looking and care about the future amenity in the neighborhood.\(^{22}\) The last term \( \epsilon_i \) is an idiosyncratic term that is known to the household, which may be correlated with other unobservables such as block amenities and individual tastes.\(^{23}\)

### 3.2 Household Problem

We model rebuilding and selling one’s property both as absorbing states. In every period, a household that has done neither \( (d_{it−1} = 0) \) can choose to move back and rebuild so that \( \{d_{it'}\}_{t'>t} = 1 \), or to sell the property so that \( \{d_{it'}\}_{t'>t} = -1 \), or to wait until the next period so that \( d_{it} = 0 \).

Given the fraction of households who have rebuilt by the end of the previous period \( (\mu_{j(i),t−1}) \) and the endogenous law of motion for future rebuilding rates \( (\Gamma_{jt}(\mu)) \), the discounted (at rate \( \beta \)) value of remaining lifetime utility for households who have already rebuilt

\(\vdots\)

---

\(^{20}\)A majority of Gulf Coast applicants to the federally subsidized SBA disaster loan program were rejected in the aftermath of Katrina (Eaton and Nixon, 2005), suggesting that many households faced restricted access to credit.

\(^{21}\)The assumption that households with risk scores above the threshold \( \rho^* \) have *unlimited* credit access \( (A_0 > -\infty) \) is less restrictive than it might seem. In our framework, the rebuilding decision is the only major investment choice that households face, so the meaningful assumption is that “unconstrained” households have sufficient credit to finance home repairs/rebuilding.

\(^{22}\)A more flexible specification would allow the price to be period-specific and to depend on all future rebuilding rates (e.g., price at time \( t \) depends on \( \{\mu_{j(i),t'}\}_{T=t}^{T} \)). We would not expect this more flexible specification to appreciably change the conclusions of our full information model, because anticipated block rebuilding trends should be capitalized into homes’ values prior to \( T \). Since this more-flexible specification would greatly complicate computation, we leave this more-flexible specification for future work.

\(^{23}\)Our estimation takes such correlations into account, as described in Section 5.
at the beginning of period $t$ is,

$$
V_{it}^d (\mu_{j(i),t-1}) = \sum_{t' \geq t} \beta^{t'-t} v_{it'} (\mu_{j(i),t';1}),
$$

(1)

s.t. $\mu_{t'} = \Gamma_{j(t')} (\mu_{t'-1})$ for all $t' \geq t$,

where the superscript on $V^d (\cdot)$ denotes the status $d \in \{1, 0, -1\}$.

The value of discounted remaining lifetime utility for households who have sold their houses by the beginning of period $t$ is,

$$
V_{it}^{-1} (\mu_{j(i),t-1}) = \sum_{t' \geq t} \beta^{t'-t} v_{it'} (\mu_{j(i),t';-1}).
$$

(2)

At each period $t \in \{1, 2, .., T\}$, households that have not rebuilt or sold their houses make their decisions after observing the fraction $\mu_{j(i),t-1}$ of neighbors who had already moved back by period $t - 1$. The value function for such a household is

$$
V_0^i (\mu_{j(i),t-1}) = \max \left\{ v_{it} (\mu_{j(i),t};0) + \beta V_{i+1}^0 (\mu_{j(i),t}), 
V_{it}^{-1} (\mu_{j(i),t-1}), 
V_{it}^1 (\mu_{j(i),t-1}) \right\}
$$

(3)

s.t. $\mu_t = \Gamma_{jt} (\mu_{t-1})$

Households who have not rebuilt by time $T$ are assumed to derive the outside-option utility from then on, so $\Gamma_{jt} (\mu_T) = \mu_T$ for all $t > T$, and

$$
V_{i,T+1}^0 (\mu_{j(i),T}) = \max \left\{ V_{it}^{-1} (\mu_{j(i),T}), \sum_{t' \geq T} \beta^{t'-T} v_{iT'} (\mu_{j(i),T};0) \right\}.
$$

Remark 2 Notice that the fraction of neighbors who rebuild $\mu_{j}$ affects both the utility associated with rebuilding and the price at which a home can be sold privately. As such, depending on the relative magnitudes of the two effects and on their interactions with household private incentives, it is possible that an increase in $\mu_{j}$ could increase the incentive to rebuild for some households and reduce that incentive for others.

3.3 Equilibrium

Definition 1 Given $\mu_{j,0}$, an equilibrium in community $j$ consists of (i) a set of optimal household decision rules $\{\{d_{it}^*(\cdot)\}_{t=1}^T\}_{i \in I_j}$, (ii) a sequence of period-specific rebuilding rates
\{\mu_{j,t}\}_{t=1}^{T}$, and (iii) laws of motion $\{\Gamma_{jt}(\cdot)\}_{t=1}^{T}$ such that,

(a) Given $\{\mu_{j,t}\}_{t=1}^{T}$, $\left\{\left\{d^{*}_{it}(\cdot)\right\}_{t=1}^{T}\right\}_{i \in I_j}$ comprise optimal decisions.

(b) The laws of motion $\{\Gamma_{jt}(\cdot)\}_{t=1}^{T}$ are consistent with individual choices such that,

$$\mu_{j,t} = \Gamma_{jt}(\mu_{j,t-1}) = \mu_{j,t-1} + \sum_{i \in I_j} I(d^{*}_{i,t} > d^{*}_{i,t-1}) \frac{1}{I} \text{ for } 1 \leq t \leq T.$$

With social spillover effects, multiple equilibria may exist (from the researcher’s point of view) on any given block. One commonly assumed equilibrium selection rule for empirical applications of equilibrium models is that agents agree on the equilibrium that maximizes their joint welfare.\(^{24}\) Although it is an assumption imposed by the researcher, we deem this equilibrium selection rule a reasonable one in the context of a game among neighbors, and apply this selection rule in our empirical analyses. A necessary step before selecting the equilibrium of interest is to compute all possible equilibria, which is feasible given the structure of our model. As a robustness check, we have re-estimated our model using a very different selection rule, one in which the equilibrium that minimizes their joint welfare is chosen. Our counterfactual experiment results remain robust, as shown in the Appendix Table A1.

**Remark 3** Unlike many dynamic programing problems where individuals are subject to contemporaneous shocks, we have assumed away uncertainty for the following reasons. First, choice reversals are rare in the data. Almost all households (over 96%) classified as rebuilding in our OPAO data stayed in New Orleans at least until the end of our sample period. Similarly, from 2011 to 2014 fewer than 2% of households changed their home address away from their pre-Katrina block after having returned.\(^ {25}\) These patterns suggest that contemporaneous shocks are weak relatively to other forces such as households’ permanent heterogeneity embedded in our model.\(^ {26}\) Second, unlike most dynamic programing models of private decisions, ours is an equilibrium model. Moreover, given the small number of households within each block, it is realistic to model each household as a big player. As a result, household-level shocks would induce aggregate uncertainty: if one household changes its decision due to an

\(^{24}\)A similar assumption is in Jia (2008), who assumes that the data is generated from an extremal equilibrium, one that is most profitable for one player.

\(^{25}\)This calculation is based on quarterly residence-location (Census block) data from the NYFRB Equifax Consumer Credit Panel database. In addition to measuring a host of personal finance variables, the database contains a panel of locations from 1999-present for a representative 5% sample of individuals in the U.S. with a credit file. The numbers reported in the text are calculated for the population who in 2004 lived in a New Orleans and had a home mortgage, the best available proxy for home ownership.

\(^{26}\)Another explanation for these patterns would be that the shocks are highly persistent, which would cause them to play a similar role as permanent heterogeneity.
unforeseen shock, the rebuilding rate and hence the equilibrium on its block also changes. Solving for the equilibrium in a model like ours with the addition of aggregate uncertainty would be infeasible: the size of the state space and belief space needed to capture this form of uncertainty is unmanageably large even for moderately sized blocks. While the strong persistence of rebuilding choices observed in the data suggests that contemporaneous shocks play a small role relative to persistent heterogeneity, ruling out uncertainty is still a strong assumption, one that we have to make in order to make this exercise feasible. However, we believe our framework, which emphasizes strategic play among individuals and its equilibrium implications for policy designs, is an important step forward. It serves as a basis for deeper and more comprehensive policy studies. We leave the incorporation of uncertainty into our framework as a future extension.

3.3.1 Tipping

Viewing a problem from an equilibrium perspective not only involves a different modeling framework than an individual decision model, it also bears important empirical implications. We discuss one of these implications, the possibility of a “tipping” phenomenon in the presence of multiple equilibria. Even though agents agree on the equilibrium that maximizes their joint welfare given the set of possible equilibria, there can still be room for policy interventions because the set of equilibria to choose from can be affected by policy. For example, a policy change may introduce a new equilibrium with a higher rebuilding rate that would not have been self-consistent otherwise, i.e., a “tipping” phenomenon, as illustrated in the appendix.

In many cases, it is both convenient and perhaps reasonable for researchers to approximate an outcome variable as a smooth function of explanatory variables. With “tipping” being a potential event, this approach may no longer be appropriate, because when “tipping” happens, there will necessarily be a “jump” in the equilibrium outcomes. Modifying the smooth function by adding certain discontinuity points may help if one knows the locations (e.g., combinations of community characteristics and policies) and the magnitude

---

To see why this is infeasible, consider household $i$ making its decision in period $t$ in a model with shocks. Household $i$ has to integrate over the joint distribution of the $I_j \times (T-t)$ shocks to all households in future periods, and if shocks are private information, it also needs to integrate over the $I_j - 1$ other households’ shocks in period $t$. The dimension of the integral is $I_j \times (T-t+1) - 1$ or $I_j (T-t)$ depending on whether or not current shocks are public information. Each realization of the vector of shocks is associated with $N^*$ number of possible equilibria, where $N^*$ is the number of possible equilibria in our current setting. (Recall all equilibria have to be computed before we can choose the equilibrium according our selection rule.) If households are heterogeneous, the number of possible equilibria to check is $N^* = 2^{I_j(T-t)}$, which with $I_j = 20$ at $t = 1$ as an example would yield an unmanageably large $N^* = 1.2 \times 10^{24}$. This exercise would need to be repeated a large number of times in order to integrate out the shocks for each candidate vector of parameter values.
of these jumps, however such information is usually not available when performing ex ante policy evaluations. Our framework lends itself toward obtaining such knowledge by explicitly modeling and solving for the equilibrium.

3.4 Further Empirical Specifications

In the following, we introduce further specifications of our model for the empirical analysis.\(^{28}\)

3.4.1 Exogenous Neighborhood Amenities

The exogenous component of block-specific amenity values are not directly observable to the researcher, and are modeled as

\[ a_{j(i)} = z_{j(i),t}' \gamma + b_{j(i)}, \]

where \( z_{j(i),t}' \gamma \) captures heterogeneity in amenity values across blocks based on pre-determined block observable characteristics \( z \), including flood exposure, pre-Katrina demographic composition, and a linear time trend to capture city-wide improvements in infrastructure. \( b_j \sim N(0, \sigma_b^2) \) is a random effect that captures heterogeneity in block amenity values that are not observable to the researcher.

3.4.2 Amenity Spillovers

The amenity spillover function is given by

\[ g(\mu) = S \times \Lambda(\mu; \lambda), \]

where the parameter \( S \) measures the total change in amenity utility associated with a block transitioning from a 0% rebuilding rate to a 100% rebuilding rate. \( \Lambda : [0, 1] \rightarrow [0, 1] \) is the Beta cumulative distribution function, with parameters \( \lambda = [\lambda_1, \lambda_2]' \). The Beta CDF is a parsimonious but flexible function that allows for a wide range of spillover patterns, as illustrated in Figure 2.

\(^{28}\)Although our identification strategy allows us to identify spillover effects non-parametrically, we impose more structure in our empirical analyses to make the estimation feasible and to conduct counterfactual analyses that inevitably involve extrapolation.
4 Data, Policy Details, and Descriptive Analyses

4.1 Data

The main data for our analysis are the administrative property records of the Orleans Parish Assessor’s Office (Assessor’s property data) and the administrative program records of the Louisiana Road Home grant program (RH data). The Assessor’s property data provide information on the timing of home repairs and home sales for the full universe of New Orleans properties. For each property, the data provide annual appraised land and structure values for 2004-2010 (Katrina occurred in 2005), which we use to infer the timing of home repairs, and the date and transaction price of all post-Katrina home sales.

The administrative program records from the RH data provide detailed information on the grant amount offered to each program applicant and a record of whether each applicant household chose a rebuilding grant (which required the household to rebuild its home and then not sell for at least three years), a relocation grant (which stipulated that the household to turn its property over to a state land trust with no additional compensation for any as-is value of the property), or chose not to participate. The data also include all of the inputs to the RH grant offer formula; including a repair cost appraisal for each home, a replacement cost appraisal for each home, and the total value of private insurance payments paid to each household. Together with the RH grant formula, such information enables us to compute both types of RH grants for each household regardless of its actual choice.

We merge the RH data to the Assessor’s property data at the property level by street address. We also obtain measures of the depth of flooding on each Census block from a FEMA-provided data set created from satellite images, and we obtain measures of the demographic composition of each Census block from the 2000 decennial Census. Because our focus is on spillover effects from homeowners’ rebuilding choices, we exclude homes that were renter-occupied when Katrina occurred and we exclude Census blocks that contained fewer than five owner occupied homes. The resulting dataset contains 60,175 homes/households living in 4,795 blocks.

Solving our model requires a measure of the wages available to each household in and away from New Orleans \( \{w_{it}, w_{it}^0\} \). Our main data sources do not contain income measures, so we impute these variables with a two step procedure that combines data from the Displaced New Orleans Residents Survey (DNORS) on the distribution of earnings and occupations in New Orleans during the year prior to Katrina and data from the American Community Survey.

\(^{29}\) Fielded by RAND in 2009 and 2010, the Displaced New Orleans Residents Survey located and interviewed a population-representative 1% sample of the population who had been living in New Orleans just prior to Hurricane Katrina.
(ACS) on occupation-specific trends in prevailing wages across labor markets from 2005-2010. The first step uses nearest Mahalanobis distance matching to assign each household a “donor” DNORS record. The second step imputes Post-Katrina wage offers by adjusting the household head’s and spouse’s pre-Katrina annual earnings by an occupation-MSA-specific wage index estimated with ACS data. A detailed description of both steps is provided in the Appendix. The imputed wage measures capture the fact that the incentive to return to New Orleans varied across households of different occupations (e.g. construction wages increased and personal service wages fell post-Katrina). Because of the extent of imputation in these variables, we do not exploit variation in labor market incentives for identification.

Lastly, we use data from the Federal Reserve Bank of New York Consumer Credit Panel / Equifax to obtain information on neighborhood-level credit conditions. These data cannot be merged at the household level to our other data sources. Instead, we compute the average Equifax risk score within 1/4 mile of each block’s centroid, and assign each household a simulated credit score \( \text{risk}_i \sim N(\overline{\text{risk}}_{\text{buf}}(i), 85) \), where \( \overline{\text{risk}}_{\text{buf}}(i) \) is the average risk-score calculated for household \( i \)’s block and 85 is the within-block standard deviation of risk scores.\(^{30}\)

### 4.1.1 Summary Statistics

Table 1 presents descriptive statistics for our sample of homeowning households (Column 1) and the subsample of households whose houses were damaged and left unlivable by Katrina (Column 2). Forty-six percent of households lived in areas that received less than 2 feet of flooding, while over 20% of households were from areas that received over 5 feet of flooding. Not surprisingly, households with damaged houses were disproportionately more likely to have lived in areas that were heavily flooded. Compared to an average household, those with damaged houses were more likely to be black, less likely to be college educated, and more likely to have lower credit scores. For an average household with a damaged house, insurance covered only 52% of repair costs. Over 60% of households with damages participated in the RH program and a vast majority of them chose the rebuilding grant option as opposed to the relocation grant option. Thirteen percent of these households rebuilt their houses within 1 year of Katrina; by the fifth anniversary of Katrina, this fraction rose to 54%.

Table 2 presents similar statistics at the block level for all blocks (Column 1) and blocks with at least one household with a damaged/unlivable house (Column 2). The same corre-

\(^{30}\)It would be ideal to allow credit scores to vary systematically by household characteristics within a block. Our cruder approach to modeling credit availability is driven by a data limitation, namely that we observe a “spatial moving average” of credit scores but not microdata. Given the high degree of both racial and economic segregation in New Orleans, however, we do not expect that conditioning credit score draws on additional observables within neighborhoods would change our results in a meaningful way.
lation between damages and demographics at the household level persists at the block level, i.e., blocks with damaged houses were more likely to be black neighborhood, to have fewer residents with college education and/or high credit scores.

### 4.2 The RH Grant Discontinuity and Post-Katrina Rebuilding

Subject to an upper limit of $150,000, RH provided grant compensation to households equal to the “value of their home damages” minus the value of any insurance payouts already received. Home damages were valued at the cost of component-by-component repairs in cases where the estimated repair cost was 51% or less of the home’s estimated full replacement cost, and at the full replacement cost otherwise. In particular, the grant offer formula was given by

\[
\text{RH Grant} = \begin{cases} 
\min \left( \frac{\text{RepairCost} - \text{Insurance Payout}}{\text{Replacement Cost}} ; \frac{\text{RepairCost}}{\text{Replacement Cost}} \right) & \text{if } \frac{\text{RepairCost}}{\text{Replacement Cost}} < 51\% \\
\min \left( \frac{\text{Replacement Cost} - \text{Insurance Payout}}{\text{Replacement Cost}} ; \frac{\text{Replacement Cost}}{\text{Replacement Cost}} \right) & \text{if } \frac{\text{RepairCost}}{\text{Replacement Cost}} \geq 51\%.
\end{cases}
\]

Our analysis exploits the fact that the size of grant offers increased discontinuously at the 51% home damage fraction (repair cost ÷ replacement cost) threshold. Assuming households could not perfectly control their appraised damage fractions, variation in grant offers very close to the 51% damage threshold can be thought of as approximately random and thus orthogonal to the sorts of unmeasured neighborhood-level variables that can confound the identification of social spillovers in purely observational settings.\(^{31}\) This policy cutoff approximates an experiment in which the private incentives of some households were experimentally manipulated without directly changing the incentives of their neighbors.\(^{32}\) Assuming households responded to private incentives, spillover effects are identified by differences between the rebuilding patterns of neighbors of households with just above versus just below 51% damage.

Figure 3 shows that the policy discontinuity did in fact discontinuously affect households’ private incentives to rebuild and in turn their private rebuilding choices. The left panel of Figure 3 plots the average opportunity cost of declining a RH rebuilding grant within

\(^{31}\)See Brock and Durlauf (2007) for a discussion of the non-identification of binary choice models with social interactions in observational settings when there are group-level unobservables, and possible approaches to partial identification in those cases.

\(^{32}\)Among households with damaged homes, 6.6% have a damage fraction within two percentage points of the 51% Road Home grant formula discontinuity, and 45% of Census blocks contain at least one such household.
damage-fraction bins.\(^{33}\)

\[
Cost_i = \overline{\text{cost}} + \Delta^{(\text{cost})} \times 1_{R_i > 0} + a_1 R_i + a_2 R_i^2 + a_3 R_i \times 1_{R_i > 0} + a_4 R_i^2 \times 1_{R_i > 0} + e_i,
\]

where \(R_i\) is Household \(i\)’s damage fraction minus .51. The right panel of Figure 3 plots the rebuilding rate as of Katrina’s fifth anniversary within damage-fraction bins,

\[
Y_i = \overline{y} + \Delta^{(y)} \times 1_{R_i > 0} + a_1 R_i + a_2 R_i^2 + a_3 R_i \times 1_{R_i > 0} + a_4 R_i^2 \times 1_{R_i > 0} + e_i. \tag{4}
\]

On average, the opportunity cost of relocating increased by $19.6k at the 51% damage threshold, and the probability of rebuilding increases by 5.0 percentage points.

### 4.2.1 Validity Tests

This quasi-experiment is only credible for studying spillover effects if households were unable to perfectly control the value of their “damage fraction” running variable relative to the 51% damage threshold. Panels (a) and (b) of Figure 4 compute McCrary tests for continuity in the density of damage fractions at 51% based on two different definitions of the damage fraction variable. The damage fraction variable summarized in panel (a) is based on households’ final damage appraisals, incorporating the adjudicated decisions on all household appeals of initial damage appraisals, and unsurprisingly exhibits a somewhat larger density just above 51% than just below 51% (\(p=.064\)). The damage fraction variable summarized in panel (b) is based on households’ initial damage appraisals. A McCrary test applied to these “first-appraisal” damage fractions fails to reject continuity at the 51% threshold (\(p=0.533\)). These patterns lead us to treat the first-appraisal damage fraction as the running variable in all of the paper’s substantive analyses. Panel (c) confirms that a non-trivial portion of the overall damage-fraction distribution falls near the 51% threshold.

Table (3) assesses the balance of pre-determined covariates above and below the 51%-damage grant threshold. Columns (1) and (2) report each variable’s mean among households with just below 51% damage and just above 51% damage, and column (3) reports the \(p\)-value of the null that the two are equal.\(^{34}\) These tests fail to reject the null of balance

\(^{33}\)For each household, the opportunity cost is defined as the smaller of the as-is value of the household’s damaged property (the opportunity cost of choosing a RH relocation instead of rebuilding grant) and the size of the household’s RH grant offer (the opportunity cost of selling privately).

\(^{34}\)Specifically, we restrict the sample to households with a damage fraction between 0.33 and and 0.67, and for each variable \(Z_i\) we estimate a flexible regression of the form,

\[
Z_i = \overline{z} + \Delta^{(z)} \times 1_{R_i > 0} + a_1 R_i + a_2 R_i^2 + a_3 R_i \times 1_{R_i > 0} + a_4 R_i^2 \times 1_{R_i > 0} + e_i
\]

Columns (1) and (2) of Table (3) report the left limit (\(\overline{z}\)) and right limit (\(\overline{z} + \Delta^{(z)}\)) of each variable’s conditional expectation as the damage fraction goes to .51. Column (3) reports the \(p\)-value associated with
for any covariates; including the fraction of same-block neighbors with undamaged homes, the fraction of block neighbors who are black, the fraction of block group neighbors with a college degree, the tract poverty rate, the nearby average Equifax credit score, and the depth of flooding. The table also assesses the balance of these covariates’ higher moments by comparing the probability of each covariate exceeding its unconditional 10th, 25th, 50th, 75th, and 90th percentiles above/below the 51% damage threshold, and again fails to reject balance in each case. Similarly, the predicted probability that a household rebuilds within 5 years of Katrina from a probit regression with all of these block characteristics included as explanatory variables (a propensity score) exhibits no jump at the 51% damage threshold. Finally, and crucially, we find no evidence that same-block neighbors damage fractions are functions of one another, which would invalidate the RD design as a framework for studying spillovers. Specifically, we fail to reject the null that the fraction of same-block neighbors with damage above 51% is the same for households whose own damage fraction is just above 51% and households whose own damage fraction is just below 51%.

4.2.2 Major Auxiliary Models: Data Evidence

Having failed to reject the validity of the grant formula RDD, we exploit the quasi-experiment to examine spillover effects from rebuilding, which will be included as auxiliary models for our structural estimation. We first measure the spatial scope of spillovers by estimating regressions of the form

\[
\mu_i^{(d)} = \mu + \Delta^{(d)} \times 1_{R>0} + a_1 R_i + a_2 R_i^2 + a_3 R_i \times 1_{R>0} + a_4 R_i^2 \times 1_{R>0} + e_i \tag{5}
\]

where \(\mu_i^{(d)}\) is the repair rate of homes located between \(d\) and \(d + .01\) miles from \(i\), and \(\Delta^{(d)}\) captures the difference between the rebuilding rate \(d\) miles from households with just above 51% damage and just below 51% damage. Figure (5) plots the estimated values of \(\Delta^{(d)}\) for \(d = 0\) to 1 miles. While the rebuilding rate of the directly subsidized households increased by 5.0 percentage points at the 51% damage threshold, the rebuilding rate of immediate neighbors’ increased by about 2.5 percentage points. That spillover effect was roughly constant with distance up to 1/3 of a mile from directly subsidized households before decaying to zero beyond that. In New Orleans, the standard Census geographic unit that best corresponds to this spatial extent of spillovers is the Census block, which leads us to null that \(\Delta^{(z)} = 0\).

35One concern \textit{ex ante} was that inspectors might have sometimes assigned identical damage estimates within blocks, causing groups of neighbors to be simultaneously affected by the discontinuous change in incentives at the grant formula discontinuity. Our balance estimates find no evidence of that kind of phenomenon.
treat a Census block as an economy in our model.\textsuperscript{36}

We next present estimates of the spillover effects of a larger private grant offer on the average rebuilding rate and on the \textit{distribution} of rebuilding rates of neighbors in the same Census block. Specifically, we estimate the regressions,

\begin{equation}
\mu_{j(i),-i} = \overline{\mu} + \overline{\Delta} \times 1_{R > 0} + a_1 R_i + a_2 R_i^2 + a_3 R_i \times 1_{R > 0} + a_4 R_i^2 \times 1_{R > 0} + e_i \tag{6}
\end{equation}

\begin{align*}
1(\mu_{j(i),-i} > .1) &= S^{(10)}(10) + \Delta^{(10)} \times 1_{R > 0} + a_1 R_i + a_2 R_i^2 + a_3 R_i \times 1_{R > 0} + a_4 R_i^2 \times 1_{R > 0} + e_i \\
1(\mu_{j(i),-i} > .2) &= S^{(20)}(20) + \Delta^{(20)} \times 1_{R > 0} + a_1 R_i + a_2 R_i^2 + a_3 R_i \times 1_{R > 0} + a_4 R_i^2 \times 1_{R > 0} + e_i \\
&\vdots \\
1(\mu_{j(i),-i} > .9) &= S^{(90)}(90) + \Delta^{(90)} \times 1_{R > 0} + a_1 R_i + a_2 R_i^2 + a_3 R_i \times 1_{R > 0} + a_4 R_i^2 \times 1_{R > 0} + e_i \tag{7}
\end{align*}

where \( j(i) \) denotes household \( i \)'s census block, and \( \mu_{j(i),-i} \) denotes the rebuilding block of \( i \)'s same block neighbors (excluding \( i \)). Because the running variable \( R_i \) is normalized to be zero at a damage fraction of 51\%, the parameter \( \overline{\mu} \) recovers the rebuilding rate of the neighbors of those with just below 51\% damage, and \( S^{(10)}, S^{(20)}, \ldots, S^{(90)} \) recover the probability that the neighbors of those with damage just below 51\% rebuild above rates of 10\%, 20\%, \ldots, 90\%.

Similarly, the parameter \( \overline{\Delta} \) recovers the difference above versus below 51\% damage in neighbors' rebuilding rate, and \( \Delta^{(10)}, \Delta^{(20)}, \ldots, \Delta^{(90)} \) recover differences above versus below 51\% damage in the probability that the neighbors rebuild at rates above 10\%, 20\%, \ldots, 90\%.

Figure (6) summarizes these results. The top panel of Figure (6) plots the rebuilding rate of households’ same-block neighbors within narrow damage fraction bins, and finds that the rebuilding rate of same block neighbors jumps by 2.4 percentage at the 51\% damage grant threshold, the point at which a household’s own probability of rebuilding increases by 5.0 percentage points. The bottom panel of Figure (6) plots the neighbors’ rebuilding rate “survivor” functions for households with just below 51\% damage (constructed from the estimated values of \( S^{(10)}, S^{(20)}, \ldots, S^{(90)} \)) and just above 51\% damage (constructed from the estimated values of \( S^{(10)} + \Delta^{(10)}, S^{(20)} + \Delta^{(20)}, \ldots, S^{(90)} + \Delta^{(90)} \)). The relatively steep slope these functions over a wide range of rebuilding rates implies that the grant discontinuity quasi-experiment occurred on blocks with a wide range of “baseline” rebuilding rates. Comparing the plots for households with above-51\% damage and below-51\% damage shows that rebuilding spillover effects operated primarily by pushing some blocks that would have experienced rebuilding below the threshold rates of 50\%, 60\%, and 70\% to experience rebuilding rates above these thresholds. This patterns suggest that an exogenous shock to rebuilding has a large effect on amenity values in areas with baseline rebuilding rates near this range.

\textsuperscript{36}In New Orleans, 98\% of Census blocks are less the 1/3 of a mile wide, the distance over which spillover effects appear to be roughly constant. On the other hand, more than half of Census block groups, the next largest geographic unit, are over 1/3 of a mile wide.
and a relatively small effects on amenity values in areas with very low baseline rebuilding rates.

5 Model Estimation

5.1 Parameters Estimated outside of the Model

To reduce computational burden, we estimate the home price offer function outside of the model. We assume the offer price one faces in the private home selling market takes the following form

$$\ln (p_i) = P_1 (p_i^s, k_i, z_j(i)) + P_2 (\mu_{-i,j(i),T}) + \epsilon_i,$$

where $P_1()$ is a flexible function specified using polynomials and interactions, and $P_2()$ is a linear spline in the rebuilding rate of same-block neighbors. OLS estimates of this equation are likely to be biased for several reasons. First, $\mu_{-i,j(i),T}$ is likely to be correlated with the residual $\epsilon_i$, because unobserved block amenities $b_{j(i)}$ that directly affect offered home prices should also affect neighbors’ rebuilding choices. Second, offered prices are only observed for households who choose to sell, which will cause selection bias if idiosyncratic household attachment $\eta_i$ is correlated with unobserved house traits $\epsilon_i$.

We use fixed effects $\chi_{\tau(i)}$ for Census tracts, a larger unit of geography nesting Census blocks, to control for unobserved block amenities, where $\tau(i)$ denotes the Census tract household $i$ belonged to. We account for selection using the Heckman (1979) two-step procedure.\footnote{A non-parametric selection-correction using a polynomial in the estimated “propensity score” ($\hat{sale}_i$) as a control function yields nearly identical results.}

We treat the RH grant formula discontinuity as the excluded instrument in a first stage probit predicting the probability of a home sale, and include the associated inverse Mills ratio as a regressor in the second stage estimating equation, such that

$$\ln (p_i) = P_1 (p_i^s, k_i, z_j(i)) + P_2 (\mu_{j(i),T}) + \rho \lambda (\Phi^{-1}(\hat{sale}_i)) + \chi_{\tau(i)} + \epsilon_i. \quad (8)$$

5.2 Parameters Estimated within the Model

The vector of structural parameters ($\Theta$) to be estimated within the model consists of the parameters governing: 1) the dispersion of household attachment ($\sigma_\eta$), 2) the exogenous block-specific amenity values ($\gamma, \sigma_b$), 3) the nature of amenity spillovers ($S, \lambda$), and 4) the credit score threshold for borrowing ($\rho^*$).

The estimation is via indirect inference, which is well-suited for estimating models like
ours that are straightforward to simulate (under any particular parameterization) but for which it is difficult to evaluate a likelihood function or a set of model-implied moments directly. This approach consists of two steps. The first step is to compute from the data a set of “auxiliary models” that summarize the patterns in the data to be targeted for the structural estimation. The second step involves repeatedly simulating data with the structural model, computing corresponding auxiliary models using the simulated data, and searching for the model parameters that cause the auxiliary model estimates computed from the simulated data and from the true data to match as closely as possible.

5.2.1 Auxiliary Models

The auxiliary models the we target include:

1. RDD estimates of the private rebuilding elasticity: specifically the parameters $\bar{\gamma}$ and $\Delta^{(y)}$ from equation (4) characterizing the left and right limits of the private rebuilding rate at the 51% damage fraction grant threshold.

2. RDD estimates of spillovers from private rebuilding choices onto neighbors’ rebuilding choices: specifically the parameters $\bar{\mu}$ and $\bar{\Delta}$ from Equation (6) characterizing the left and right limits of a household’s neighbors’ rebuilding rate at the 51% damage fraction grant threshold, and the parameters $\mu^{(p)}$ and $\Delta^{(p)}$ from equations (7) for $p = 10, 20, ..., 90$ characterizing the left and right limits of the likelihood that a household’s neighbors’ rebuilding rate exceeds each threshold at the 51% damage fraction grant threshold.

3. Descriptive regressions of year $t$ private rebuilding indicators on block flood exposure and average block credit scores for $t=1,...,5$.

5.2.2 Estimation Algorithm

Our estimation algorithm involves an outer loop searching over the space of structural parameters, and an inner loop that computes auxiliary models using simulated data from the structural model.

The Inner Loop With simulated data, computing auxiliary models is straightforward and follows the same procedure as described above. We focus on describing the solution to the model, given a set of parameter values $\Theta$. Given $\Theta$, for each community $j$ observed in the data, simulate $N$ copies of communities $j_n$ that share the same observable characteristics but differ in unobservables, at both the individual and the community level. The unobservables
are drawn from the distributions governed by \((\sigma_\eta, \sigma_b)\). For each simulated community, solve for the equilibrium as follows, where we suppressing the block subscript \(j\).

1. For each block, locate all possible “self-consistent” period \(T\) block rebuilding rates by repeatedly (for each \(n_T = 1, \ldots, I\)), guessing that \(n_T/I\) is the rebuilding rate, computing the implied offered price for each household \(p_i = P(p^*_s, k_i, z_{j(i)}, \mu_{j,T} = n_T/I)\), counting the number of simulated block households \(n^*_T(n_T; \Theta)\) who prefer to rebuild when \(\mu^*_j = n_T/I\), and deeming \(\mu^*_j = n_T/I\) self consistent if \(n^*_T(n_T; \Theta) = n_T\).

2. Select the self-consistent \(\mu_{j,T}\) that maximizes total block welfare \(W_{T-1} = \sum_i V_{i,T-1}\). Store the associated offered price for each household.

3. Taking equilibrium home prices as given, locate all possible “self-consistent” period \(T-1\) block rebuilding rates by repeatedly (for each \(n_{T-1} = 1, \ldots, I\)), guessing that \(n_{T-1}/I\) is the rebuilding rate, counting the number of simulated block households \(n^*_{T-1}(n_{T-1}; \Theta)\) who prefer to rebuild when \(\mu^*_{j,T-1} = n_{T-1}/I\), and deeming \(\mu^*_{j,T-1} = n_{T-1}/I\) self consistent if \(n^*_{T-1}(n_{T-1}; \Theta) = n_{T-1}\).

4. Select the self-consistent \(\mu_{j,T-1}\) that maximizes total block welfare \(W_{T-1} = \sum_i V_{i,T-1}\).

5. Repeat steps 3 and 4 for \(t = T-2, T-3, \ldots, 1\).

**The Outer Loop**

Let \(\bar{\beta}\) denote our chosen set of auxiliary model parameters computed from data. Let \(\hat{\beta}(\Theta)\) denote the corresponding auxiliary model parameters obtained from simulating \(S\) datasets from the model (parameterized by a particular vector \(\Theta\)) and computing the same estimators. The structural parameter estimator is then the solution

\[
\hat{\Theta} = \arg\min_\Theta \left[ \hat{\beta}(\Theta) - \bar{\beta} \right]^TW[\hat{\beta}(\Theta) - \bar{\beta}],
\]

where \(W\) is a weighting matrix. We obtain standard errors for \(\hat{\beta}(\Theta)\) by numerically computing \(\partial \hat{\Theta}/\partial \bar{\beta}\) and applying the delta method to the variance-covariance matrix of \(\bar{\beta}\).

We augment the indirect inference strategy with an importance sampling technique suggested by Sauer and Taber (2012) that ensures a smooth objective function even though the procedure is simulation-based and the model outcomes are discrete.

**5.3 Identification**

Although all of the structural parameters are identified jointly, relying on the information summarized in the entire set of auxiliary models, we provide a sketch of identification here by describing which auxiliary models are most informative about certain structural parameters.
5.3.1  $\sigma_\eta$, $\sigma_b$, and $g(\mu)$

First consider how the parameters governing the unobserved heterogeneity in households’ payoffs ($\eta$, $b$, and $g(\mu)$) are separately identified. The logic follows three steps. We first explain how the dispersion of the combined term $\eta + b + g(\mu)$ is identified, then how the variance of idiosyncratic heterogeneity $\eta$ is identified separately from the variance of block-level heterogeneity $(b + g(\mu))$, and finally how the amenity spillover function $g(\mu)$ is identified in the presence of unobserved block-level heterogeneity $b$.

The elasticity of rebuilding with respect to private financial incentives is governed primarily by the dispersion of unobserved heterogeneity across all households in preferences for rebuilding. A household’s own rebuilding decision follows a threshold rule based on whether or not $\eta + b + g(\mu)$ exceeds a particular value. All else equal, rebuilding choices will be less price-elastic if unobserved heterogeneity is more disperse, because any given change in the utility threshold for rebuilding caused by a change in financial incentives sweeps over a smaller fraction of unobserved heterogeneity. The dispersion of $\eta + b + g(\mu)$ is thus identified mainly from the size of RDD parameter $\Delta^g$, the difference between the rebuilding rates of households with damage levels just above versus below the RH grant formula discontinuity, relative to the change in incentives $\Delta^{cost}$ across the grant threshold.

Next consider how the distribution of idiosyncratic heterogeneity, characterized by $\sigma_\eta$, is identified separately from the distribution of block-level heterogeneity, characterized by $\sigma_b$ and $g(\mu)$. The relative variance of idiosyncratic and block-level heterogeneity governs the dispersion of rebuilding rates across blocks. If the variance of $(b + g(\mu))$ is small, unobserved heterogeneity in payoffs will be mostly idiosyncratic to households within blocks, and blocks with similar observable fundamentals will experience similar rebuilding rates (i.e. $\mu_j$ will have a relatively small variance conditional on observables). If the variance of $(b + g(\mu))$ is large,

\[ b_{j(i)} + \eta_i + \left( \frac{1 - \beta}{\beta^5 - \beta^9} \right) g(\mu_{j(i),5}) > \left[ \frac{1 - \beta}{\beta^5 - \beta^9} \right] \max_{c_{it}} \left\{ \sum_{t=1}^8 \ln c_{it} \left| \text{does not rebuild} \right. \right\} - \left[ \left( \frac{1 - \beta}{\beta^5 - \beta^9} \right) \max_{c_{it}} \left\{ \sum_{t=1}^8 \ln c_{it} \left| \text{rebuild at } t = 5 \right. \right\} + Z'_{j(i)} \gamma \right] \]

In principle, variation in other financial incentives like private insurance settlements, the market values of households’ properties, and the prevailing wages in post-Katrina New Orleans in household members’ pre-Katrina occupations could aid in identification. We rely, instead, on the RD variation in financial incentives for identification, because we expect that differences across households in these other financial incentives to be correlated with households’ idiosyncratic attachment to home and/or the unobserved amenities in households’ neighborhoods. On the other hand, while households with damages on either side of the RH grant formula threshold faced significantly different incentives to rebuild, they faced similar distributions of $\eta$ and $b$. 

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38 For example, a household would prefer to rebuild in period 5 versus not rebuilding if,

39 In principle, variation in other financial incentives like private insurance settlements, the market values of households’ properties, and the prevailing wages in post-Katrina New Orleans in household members’ pre-Katrina occupations could aid in identification. We rely, instead, on the RD variation in financial incentives for identification, because we expect that differences across households in these other financial incentives to be correlated with households’ idiosyncratic attachment to home and/or the unobserved amenities in households’ neighborhoods. On the other hand, while households with damages on either side of the RH grant formula threshold faced significantly different incentives to rebuild, they faced similar distributions of $\eta$ and $b$. 

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there will be large differences between blocks with similar observable fundamentals in the average payoff to rebuilding, and \( \mu_j \) will have a larger variance conditional on observables. The variance of \( \eta \) (i.e. \( \sigma_\eta \)) is thus separately identified from the variance of \( (b + g(\mu)) \) mainly by the auxiliary model parameters \( S^{(10)}, S^{(20)}, \ldots, S^{(90)} \) measuring the CDF of block rebuilding rates among households in a particular pre-determined circumstance.

Next consider how the spillover function \( g(\mu) \) is identified separately from the distribution of exogenous block-level amenities \( b \). The spillover function \( g(\mu) \) governs the effect of one household rebuilding on its neighbors’ incentive to rebuild, and, as a result, the extent to which private incentives will generate spillover effects. A private incentive for particular households to rebuild will have larger spillover effects on the choices of neighbors when \( g(\mu) \) is steeper. These spillover effects will only occur on blocks where the damage levels are within particular ranges (not necessarily connected) if \( g(.) \) is sufficiently nonlinear, while spillovers will occur similarly across all blocks if \( g(.) \) is approximately linear. The identification challenge is that unobserved group-level variables such as \( b \) also cause neighbors to behave similarly, so inferring spillover effects in this way is invalid if households’ financial incentives are correlated with \( b \). We solve this identification challenge by exploiting the variation in financial incentives generated by the RH grant discontinuity, variation which is as-good-as random and thus orthogonal to \( b \).

In particular, the amplitude and shape of a general non-decreasing smooth amenity spillover function \( g(\mu) \) are identified by spillovers from the discontinuously higher RH grant offers made to households with damages just above versus just below the RH grant formula threshold \( (\Delta, \Delta^{(10)}, \ldots, \Delta^{(90)}) \), compared to the direct effect of those higher grant offers on private rebuilding choices \( (\Delta^y) \). Under our parameterization of the amenity spillover function, \( g(\mu; S, \lambda_1, \lambda_2) \), the amplitude of \( g(\mu) \) is governed by the parameter \( S \), and the shape of \( g(\mu) \) is governed by the parameters \( \lambda_1 \) and \( \lambda_2 \). The average spillover measure \( \bar{\Delta} \) is therefore particularly informative about the value of \( S \), and the pattern of spillovers onto the probabilities that neighbors’ rebuilding rates exceed the different thresholds \( (\Delta^{(10)}, \ldots, \Delta^{(90)}) \) is particularly informative about the values of the shape parameters \( \lambda_1 \) and \( \lambda_2 \).

**Remark 4** This identification strategy combines two strands of identification arguments. On the one hand, it is a standard identification argument from the social interactions literature that the strength of social interactions can be identified by comparing a private incentive’s spillover effects and direct effects (e.g. Brock and Durlauf 2001 and 2007). On the other hand, we separate the spillover effects from unobserved neighborhood amenities by exploiting the discontinuity in the grant formula, which is similar in spirit to the quasi-experimental or “design-based” strategies that are commonly used in the program evaluation literature to recover “treatment effects,” though the estimands in our framework are the structural
parameters of an economic model.

5.3.2 Other Parameters

The credit risk cutoff parameter $\rho^*$ determines the fraction of households in each neighborhood who are borrowing constrained. Because most RH grants were paid more than two years after Hurricane Katrina, the prevalence of borrowing constraints strongly influences the predicted timing of rebuilding. For households who were borrowing constrained, the self-financing of home repairs prior to RH grants being disbursed would have entailed a significant reduction to lifetime consumption utility, forcing them to delay rebuilding. For households who were able to borrow, consumption would be smooth across periods regardless of the timing of repairs. The parameter $\rho^*$ is thus mainly identified by the extent to which the repair rate hazard increased after the disbursement of RH grants across neighborhoods with different mean Equifax risk scores.

Finally, the parameters $\gamma$ describing exogenous differences in amenity values across flood categories are identified by differences in rebuilding rates across flood categories beyond what would be predicted by households’ private incentives.

6 Results

6.1 Parameter Estimates

Table 4 presents the estimated structural parameters, beginning with the parameters that characterize the spillover effects of rebuilding. To illustrate the spillover effects, we plot the estimated spillover function $g(\mu)$ in the top panel of Figure (7). Fully rebuilding a block increases its flow amenity valuation by the equivalent of a 43 log-point increase in annual non-housing consumption. However, the incremental impact of additional rebuilding depends critically on the block’s initial rebuilding rate. The marginal impact of rebuilding on a block’s amenity value is close to zero in areas with rebuilding rates below 50%; yet it is substantial in areas with rebuilding rates above 50%. The bottom panel of Figure (7) plots the estimated effect of a block’s rebuilding rate on house offer prices, i.e., the spline in $\mu_{-i}$ from estimating equation (8). A home’s price increases by nearly 20% if all of the homes on its block are rebuilt by Katrina’s fifth anniversary ($\mu_{-i} = 1$ relative to $\mu_{-i} = 0$). As is true for amenity spillovers, the marginal impact of rebuilding on home prices is the highest in areas with the highest rebuilding rate.

The next panels of Table 4 characterize the exogenous components of block amenities, including the components that are determined by observable factors ($z_{j,t}\gamma$) and the compo-
ment that is not observable \( (b_j) \). An estimated set of year-specific utility intercepts increases monotonically with time, presumably reflecting city-wide infrastructure repairs. Coefficient estimates on a set of block flood-exposure categories do not exhibit a clear pattern, suggesting that a block’s amenity value is not strongly correlated with its flooding risk per se. We find significant heterogeneity in the unobserved component of blocks’ flow amenity values \( (\sigma_b = 0.39) \). In comparison, the cross-block standard deviation of equilibrium amenity levels net of unobservables \( (z_j^r \gamma + g(\mu, t)) \) is 0.41 at \( t = 1 \), and 0.46 at \( t = 5 \). The standard deviation of households’ idiosyncratic attachment \( (\sigma \eta) \) is 0.60 log-consumption points, which is 12.9% of the average log consumption level across all households.

Finally, our estimated Equifax credit score threshold \( (\rho^*) \) for securing a rebuilding loan is 678.5. This threshold is considerably higher than the commonly-cited “rule of thumb” cutoff of 620 for securing a standard mortgage (Keys, Mukherjee, Seru, and Vig 2008), and thus is consistent with the fact that the federally-subsidized SBA Disaster Loan program rejected a large majority of applicants from the Gulf Coast in the aftermath of Katrina (Eaton and Nixon, 2005).

### 6.2 Model Fit

Figure (8) illustrates the model’s fit to the RD parameters that we targeted as auxiliary models. The model closely replicates the difference between the rebuilding rate of households with just below 51% damage and just above 51% damage \( (\Delta^{(9)} \text{ from equation (4)}) \). The model also replicates the difference in the mean and distribution of same-block-neighbor rebuilding rates between households with just below 51% damage and households’ with just above 51% damage \( (\Delta \text{ from equation (6)} \text{ and } \Delta^{(10)} \ldots, \Delta^{(90)} \text{ from equation (7)}) \).

Figures (9) illustrates the model’s fit to rebuilding trends, for the full sample, by block flood exposure and by average neighborhood Equifax credit scores. Overall, the model fit is good. It captures many of the major differences in rebuilding trends, which are not directly targeted during the estimation. However, the model under-predicts the rebuilding rates for areas with 3-4 feet and over 6 feet of flooding. As shown in Figure (10), the model fits well to the distribution of block rebuilding rates five years after Katrina, for both the full sample and subcategories defined by block flood exposure and average neighborhood Equifax credit scores.
7 Counterfactual Policy Simulations

We conduct three sets of counterfactual policy analyses. The first decomposes the full impacts of RH into its impact via private financial incentives alone and its impact via amenity spillovers. The second contrasts the welfare effects of RH with those under unconditional grants. Finally, we explore the potential for improvement in the design of conditional subsidies.

7.1 RH’s Direct Effects and Feedback Effects

To measure the importance of the “feedback” effects from amenity spillovers, we compare the full equilibrium impact of RH with the impact generated by the program’s financial incentives alone (holding amenities fixed). To begin, we simulate equilibrium rebuilding choices without RH grants. We then simulate the impact of introducing RH’s financial incentives while holding amenity values fixed, which boils down to an individual decision model without spillovers. Finally, we simulate our equilibrium model with endogenous amenity values, which measures the full equilibrium impact of RH.

Table (5) reports the impacts of RH on rebuilding rates, without and with amenity spillovers, as of Katrina’s 5th anniversary. RH’s private incentives increased the rebuilding rate by 6.3 percentage points, from a rate of 61.7% without grants. RH’s full equilibrium impact was 1.7 percentage points larger, implying an average multiplier effect of 1.27 (8.0/6.3). The direct RH effect from private financial incentives and the equilibrium multiplier were both larger in areas that suffered from moderate flooding (between 2 and 5 feet), relative to areas with the least and the most severe flooding. Comparing areas with different rebuilding rates without RH, we find that the impact of RH decreases with an area’s no-grant rebuilding rate. Yet, consistent with the spillover function estimates, the equilibrium multiplier increases with an area’s no-grant rebuilding rate.

7.2 Welfare Effects of RH versus Unconditional Grants

The RH grant program discouraged households from relocating by requiring relocating households to give their properties to a state land trust. Compared to unconditional transfers, conditional transfers such as RH entail an efficiency loss or “excess burden” for households whose choices are distorted by the conditions associated with the transfer. However, when considered in an equilibrium framework with spillovers, the conditional nature of the RH transfer may improve total welfare if the value of the positive externality generated by RH-induced rebuilding exceeds the private losses from the program’s distortion.
To study the welfare consequences of RH’s conditional structure, we compare the RH equilibrium outcomes with those under an unconditional grant program that pays a grant computed with the RH rebuilding grant formula to all households regardless of their choices. We compute the equivalent variation ($EV_{i}^{RH}$) necessary to make a household’s equilibrium welfare under the unconditional grant policy equal to that under RH, which measures households’ utility difference under the two policies in dollars.\(^\text{40}\) To account for the difference in subsidies granted in two programs, we compute household-level net welfare impacts ($dW_{i}^{RH}$) by subtracting the change in program costs, i.e.,

$$dW_{i}^{RH} = EV_{i}^{RH} - (Grant_{i, RH} - Grant_{i, Uncond}). \quad (9)$$

Table (6) summarizes the results. Column (1) reports the fraction of households who were “marginal” in the sense that their rebuilding choices under RH differed from what they would have made under the unconditional grant policy. Of all households, 9.1% were at the margin. This fraction was the smallest (4.8%) in the least flooded areas and highest in moderately flooded areas. The next three columns show the net welfare impacts of RH relative to the unconditional grant ($dW_{i}^{RH}$) for inframarginal, marginal and all households, respectively.\(^\text{41}\) For an average inframarginal household, welfare improved by $4,950 as the result of the conditional grant structure that induced positive spillovers from the rebuilding of marginal households. An average marginal household, however, was worse off by an equivalent of $24,360. Overall, RH increased average household welfare by $2,177 ($131M in total), relative to the unconditional grant policy. Except for areas with 5-6 feet of flooding, where a $475 loss occurred, welfare improved across areas with different flooding exposures. The improvement was particularly significant in moderately flooded areas, which is consistent with our previous finding that RH’s impacts on rebuilding rates were larger in these areas.

**Remark 5** Our calculation of $dW_{i}^{RH}$ does not take into account the value of properties

\(^\text{40}\)Specifically, we find the dollar amount that when paid as a constant per-period flow from $t = 1, ..., T$ under the unconditional grant policy provides household $i$ the same discounted lifetime utility $i$ receives in equilibrium under RH. Letting $ev_i$ denote the per-period payment, our equivalent variation measure $EV_i$ is the present discounted value of this stream,

$$EV_i = \left(\frac{ev_i}{r}\right)\left(1 - \frac{1}{(1 + r)^{T+1}}\right)$$

\(^\text{41}\)Compared to an unconditional grant policy, a policy that offers smaller grants to households who do not rebuild can affect a household’s welfare (measured in dollars) in three ways: (1) change the household’s equilibrium property value, (2) change the non-pecuniary utility the household derives from it’s equilibrium location choices (measured as an equivalent variation), and (3) reduce the size of a household’s grant payment (for inframarginal non-rebuilding households). Because item (3) is an equal-sized benefit to the government, the total change to social welfare is the sum of (1) and (2).
turned over to the state by RH relocation grant recipients. Before Katrina, the total value of the land on which these properties sat (appraised by the parish Assessor’s Office for property tax purposes) was $54M. Assigning this value to the properties in the welfare calculation would increase the calculated per capita “government savings” from RH compared to the unconditional grant program by $908 (= $54M / 60,175). While we do not have reliable data on the post-Katrina value of these properties, we expect the value to be substantially lower than $54M, because the properties are located disproportionately in areas of the city that received heavy flooding and in the neighborhoods that were slowest to rebuild.\footnote{More than 70\% of relocation grant recipients are from blocks that received more than 4 feet of flooding, and the fraction of homes in these neighborhoods repaired by the pre-Katrina owner within 5 years was just 35\%.}

7.3 The Optimal Generosity of Relocation Grants

We have shown that RH, which is a particular form of conditional subsidy policy, improved average household welfare by $2,177 relative to an unconditional grant policy. In the following, we examine the potential for further model-guided improvements by exploring a particular form of conditional subsidy policies: we take as given the RH rebuilding grant formula and make the relocation grant a fraction $(1 - \rho)$ of that of the rebuilding grant, but without the requirement that relocating households turn their property over to a state land trust. We consider different constraints on how flexibly the policymaker may vary $\rho$; and for a given constraint, we search for the vectors of $\rho$’s that maximize the equilibrium average net welfare. The constraints we consider require, respectively, that a uniform $\rho$ be applied to all households, and that a uniform $\rho$ be be applied to all households within each subgroup defined by different criteria including 1) block-level demographics, 2) the fraction of households with damaged houses living in a block, 3) block-level flood exposure, and 4) the interaction of 2) and 3).\footnote{Criterion 1) defines 28 groups by the cross product of $I (P(\text{black}) > 0.5), I (P(\text{college-educated}) > 0.5)$ and average credit score category. Criterion 2) defines 10 groups with the fractions <10\%, 10-20\%, ..., 90-100\%. Criterion 3) defines 6 groups.} In addition, we also consider a case where $\rho$’s are allowed to be block-specific.

\textbf{Remark 6} We conduct a particular set of counterfactual policies for illustration. However, one could use our framework to examine a much broader set of counterfactual policies. For example, we use total welfare as our criterion for optimal policies; yet our model can be easily used to evaluate policies based on other criteria. Similarly, we only consider a particular subset of conditional subsidy policies. Given a different policy space defined by specific institutional constraints, one could use our model to search for optimal policies accordingly. In particular, larger welfare gains would be expected if a broader policy space is explored.
Table 7 summarizes the welfare consequences of the different subsidy policies, where the impacts are presented separately on household welfare, government savings, and net welfare, i.e., the counterparts of $EV_{i,RH}^{RH}, (Grant_{i,RH} - Grant_{i,Uncond})$ and $dW_{i,RH}$ as defined in (9) but for the policies we consider. Relative to the welfare level under the unconditional grant policy, savings in grant funds dominates the household welfare changes under the uniform conditional subsidy policy, which increases the net average household welfare by $2,648. Targeting based on block demographics and on the fraction of blocks’ homes that were damaged both improve upon the uniform subsidy, but only by about $300 and $400, respectively. While targeting based on flood-exposure categories yields smaller reduction in government expenditures, the approach yields substantially smaller private welfare losses for households, and generates larger net welfare improvements of $3,613 per household relative to the unconditional policy.

The most interesting result comes from block-specific subsidies, which not only save government grant money, but also improve household welfare, leading to a net welfare increase of $6,000 per household. It is worth noting that in the absence of externalities, a distorting conditional subsidy policy could not improve household welfare relative to an unconditional subsidy policy. In the presence of externalities, not only can carefully-designed conditional subsidies improve household welfare, but also at lower government costs, leading to a “win-win” scenario.

To illustrate the nature of the optimal policies, Figure 11 shows the optimal block-specific penalty $\rho$ by block-level flood exposure and the block-level home-damage rate. The relationship is inversed-U-shaped, with higher penalties in moderately damaged/flooded neighborhoods. The optimal policy heavily penalizes ($\rho > 50\%$) relocation in neighborhoods with moderate damage rates and/or flood exposure, as those neighborhoods tend to have many households close to the margin regarding the choice to rebuild and are ones where additional rebuilding generates substantial positive externalities for inframarginal households. In contrast, relatively few households are close to being marginal in neighborhoods that received very light or very severe damages, so it is optimal to provide grants with few strings attached for households from those neighborhoods.

8 Conclusion

Many housing policies are predicated on the idea that housing investments generate positive externalities. The optimal design of these policies requires an understanding of the nature of these externalities, the decision making processes of individual households, and the way those decisions intertwine in equilibrium. Toward that end, we have developed a frame-
work that combines the strength of quasi-experimental research designs and the strength of structural equilibrium modeling. We have applied this framework to the case of post-Katrina reconstruction. The quasi-experimental variation in private financial incentives that we exploit for identification admits a causal interpretation of both the direct effects of RH financial incentives on rebuilding and of the spillover effects of those incentives onto neighbors’ rebuilding choices. Our equilibrium model replicates these internally-consistent causal relationships and other patterns not directly targeted for identification.

We have found that rebuilding caused economically important amenity spillovers: the distorting RH program led to higher welfare compared to an unconditional subsidy policy. We have illustrated how our framework can inform the design of optimal subsidy policies, which further improve household welfare while saving government costs, compared to unconditional subsidies. Such a “win-win” situation would be an implausible prediction if researchers were to treat household decisions in isolation.

Although our empirical application focuses on a special event and a particular source of identifying variation, our equilibrium modeling framework for studying private investment choices in equilibrium can be applied/extended to other cases where individual decisions inter-relate due to spillover effects. Our strategy for identifying such models using quasi-experimental variation is also promising for studies that aim at shedding light on policy designs with relatively less restrictive modeling assumptions for identification.

Several interesting extensions to our framework are worth pursuing. The first one is to embed our model into a more general equilibrium framework that considers equilibrium interactions within an entire city or region. A more general framework would also model equilibrium in the labor market, allowing for the possibility of downward sloping local labor demand (e.g., Albouy 2009, Roback 1982) conditional on population and the possibility that changes to the size of the local population shifts the local labor demand curve. Identifying these more general equilibrium models, however, would require data from multiple markets.

Another extension is to incorporate other spatially-biased policies and consider them simultaneously with the rebuilding grant policy. The existence of other distortive policies may lead to situations where the number of households living in certain areas is inefficiently high prior to a disaster occurring. This could happen due to, for example, moral hazard resulting from the precedent of generous post-disaster bailouts (Gregory 2014) or the federal income tax code’s relatively favorable treatment of less productive places (Albouy 2009, Colas and Hutchinson 2015). Although existing estimates of these distortive effects are relatively small compared to the direct incentives for locating in particular cities and neighborhoods following some disasters, optimal rebuilding grant policies may differ depending on whether or not these other existing distortions are accounted for.
References


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Appendix I. Illustration of “Tipping”

Figure (1) illustrates the phenomenon of “tipping.” The top panel of Figure (1) plots a hypothetical private demand schedule for rebuilding evaluated at the amenity level associated with a 0% rebuilding rate and the actual marginal benefit curve.\footnote{The private demand curve is downward sloping by definition as it is simply a highest-to-lowest ordering of individual households’ net benefits to rebuilding. The actual marginal benefit curve incorporates each additional household’s positive contribution to block amenities and can thus be downward or upward sloping.} Self-consistent rebuilding rates are the zeros of the latter curve. Tipping is shown in the bottom panel, where a subsidy causes additional higher rebuilding rates to become self-consistent.

Appendix II. Data Imputations

To solve our model numerically, we must impute values for several of the model’s exogenous variables we do not observe in our estimation dataset, which covers the full universe of homeowning households in New Orleans when Katrina occurred. This appendix describes our imputation procedures.

II.1 Wages

We impute a New Orleans annual household earnings offer (i.e. the wage offer $w_{1i}$) and an “outside option” annual household earnings offer (i.e. the wage offer $w_{0i}$) for each household using geocoded microdata on households’ pre-Katrina labor earnings from the Displaced New Orleans Residents Survey (DNORS)\footnote{Fielded by RAND in 2009 and 2010, the Displaced New Orleans Residents Survey located and interviewed a population-representative 1% sample of the population who had been living in New Orleans just prior to Hurricane Katrina.} and information about occupation-specific differences in prevailing wages across labor markets and across time from the 2005-2010 American Community Survey. The procedure involves two steps. In the first step we match each household in our dataset to a “donor” DNORS record using nearest Mahalanobis distance matching on a set of variables that are available for all households,\footnote{To allow us to match based on the OPAO property record variables that we observe for all households, we first merged the DNORS data with respondents’ OPAO property records. We then performed the matching procedure, matching on the following variables; appraised pre-Katrina home values, pre-Katrina neighborhood demographic variables, block-level flood exposure, the extent of Katrina-related home damages measured by the decline in appraised home values from 2005 (prior to Katrina) to 2006, indicators for whether and when post-Katrina home repairs occurred, and indicators for whether and when a home was sold after Katrina.} and impute to each record the labor market variables (household head and spouse’s occupations and pre-Katrina annual earnings) of its DNORS...
donor record. We then compute $w^0_i$ and $w^1_i$ using the expressions,

$$
w^0_i = w_{i,t<0}^{\text{head}} \left( \frac{\exp(\theta^0_{\text{occ}(i,\text{head}),t<0})}{\exp(\theta^1_{\text{occ}(i,\text{head}),t<0})} \right) + w_{i,t<0}^{\text{spouse}} \left( \frac{\exp(\theta^0_{\text{occ}(i,\text{spouse}),t<0})}{\exp(\theta^1_{\text{occ}(i,\text{spouse}),t<0})} \right)
$$

$$
w^1_i = w_{i,t<0}^{\text{head}} \left( \frac{\exp(\theta^1_{\text{occ}(i,\text{head}),t<0})}{\exp(\theta^1_{\text{occ}(i,\text{head}),t<0})} \right) + w_{i,t<0}^{\text{spouse}} \left( \frac{\exp(\theta^1_{\text{occ}(i,\text{spouse}),t<0})}{\exp(\theta^1_{\text{occ}(i,\text{spouse}),t<0})} \right)
$$

where $w_{i,t<0}^{\text{head}}$ is the household head’s pre-Katrina annual earnings, $w_{i,t<0}^{\text{spouse}}$ is his or her spouse’s pre-Katrina annual earnings (zero if the household head is single), and the terms $\theta_{\text{occ},\tau}^m$ are log-wage indices estimated with data from the 2005-2010 ACS specific to labor markets $m \in \{0, 1\}$ (with $m = 0$ referring to the “outside” option, defined as the pooled group of all metro areas in the Census-defined South region – the typical destination of households displaced from New Orleans – and $m = 1$ referring to New Orleans) and time periods $\tau$ (with $\tau < 0$ referring to pre-Katrina wages and $\tau > 0$ referring to post-Katrina wages).

II.2 Non-Housing Assets

We impute an initial asset holding ($A_{it=0}$) for each household using asset data from Displaced New Orleans Residents Survey and the 2005 Panel Study of Income Dynamics. First, using data from the PSID, we estimate a flexible statistical model of the distribution of non-housing assets conditional on a household’s observable characteristics. We use a logistic regression to estimate the probability that a household has zero liquid assets conditional the household’s observable traits, and we estimate a sequence of 99 quantile regressions (one for each quantile 1 to 99) to recover the distribution of assets conditional on the asset holding being positive. Then, using this estimated asset model, we draw 500 simulated asset holdings for each DNORS household from the conditional distribution of assets given the household’s observable characteristics. Lastly,

47The composition adjusted log-wage indices $\theta_{\text{occ},\tau}^m$ are the estimated 2-digit occupation by time period (either pre-Katrina or post-Katrina) by labor market (New Orleans or the pooled “other metro South”) fixed effects from the regression,

$$
\ln(earn_{i,\tau}) = X'_{i,\tau}a + \theta_{\text{occ}(i,\tau),\tau}^m + e_{i,\tau}
$$

where $earn_{i,\tau}$ is a worker’s annual labor earnings, measured in the 2005-2010 ACS, and $X$ is a vector of flexibly interacted demographic and human capital variables.

48Liquid assets are defined to be the sum of a household’s of non-IRA stock holdings, bond holdings, and holdings in checking accounts, savings accounts, money market accounts, and CDs.

49The explanatory variables include; indicators for solo-female headed household, solo-male headed household, the more educated household head being a high school dropout, the more educated household head having attended college but not received a bachelor’s degree, the more educated household head having a bachelor’s degree, a household head being black, the household residing in an urban area, the household residing in the south, an interaction of southern and urban, indicators for each of the four highest housing value quintiles, the age of the male head if present and the female head’s age otherwise, and the square of the age of the male head if present and the square of the female head’s age otherwise. When linking these estimates back to DNORS households, all DNORS households are classified as Southern and urban. The other inputs depend on the household’s survey responses.

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we match each household in our analysis dataset to a “donor” DNORS record using nearest Mahalanobis distance matching on a set of variables that are available for all households, and impute to each record a random draw from the DNORS donor record’s simulated asset distribution.

II.3 Home Damages for Non-Road Home Households

Lastly, we impute home replacement cost estimates and home repair cost estimates for households who did not apply to RH (and thus did not undergo RH damage appraisals). We first impute estimated replacement costs using the predicted values from a regression estimated among RH applicants of the log RH replacement cost estimate on log pre-Katrina appraised home value, pre-Katrina neighborhood demographic traits, and flood exposure. We then impute a damage fraction using the predicted estimate from nonlinear least squares estimates \( r^2 \approx .9 \) of the statistical model:

\[
\text{DamageFraction}_i = \frac{\exp(\tilde{X}'_i a)}{1 + \exp(\tilde{X}'_i a)}
\]

where \( \tilde{X}_i \) includes a polynomial in flood exposure, a polynomial in the percentage drop in the OPAO appraised value, and interactions of the two. Note that this imputation model is a smooth function of continuously distributed exogenous variables, and thus imputed records for nonapplicants do not contribute to any observed “jumps” in outcomes at the 51% grant formula threshold.

\footnote{To allow us to match based on the OPAO property record variables that we observe for all households, we first merged the DNORS data with respondents’ OPAO property records. We then performed the matching procedure, matching on the following variables; appraised pre-Katrina home values, pre-Katrina neighborhood demographic variables, block-level flood exposure, the extent of Katrina-related home damages measured by the decline in appraised home values from 2005 (prior to Katrina) to 2006, indicators for whether and when post-Katrina home repairs occurred, and indicators for whether and when a home was sold after Katrina.}
Table 1: Descriptive Statistics, Households

<table>
<thead>
<tr>
<th>Variable</th>
<th>All HHs</th>
<th>HHs with initially damaged homes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Demographic composition:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Percent black (Census block)</td>
<td>57</td>
<td>65</td>
</tr>
<tr>
<td>Percent college educated (Census tract)</td>
<td>51</td>
<td>49</td>
</tr>
<tr>
<td>Pre-Katrina block flood exposure:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt; 2 feet</td>
<td>46</td>
<td>23</td>
</tr>
<tr>
<td>2 - 3 feet</td>
<td>12</td>
<td>16</td>
</tr>
<tr>
<td>3 - 4 feet</td>
<td>11</td>
<td>16</td>
</tr>
<tr>
<td>4 - 5 feet</td>
<td>10</td>
<td>15</td>
</tr>
<tr>
<td>5 - 6 feet</td>
<td>6</td>
<td>9</td>
</tr>
<tr>
<td>&gt; 6 feet</td>
<td>15</td>
<td>21</td>
</tr>
<tr>
<td>Equifax risk score (spatial moving average):</td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;600</td>
<td>20</td>
<td>21</td>
</tr>
<tr>
<td>600-625</td>
<td>17</td>
<td>18</td>
</tr>
<tr>
<td>625-650</td>
<td>17</td>
<td>18</td>
</tr>
<tr>
<td>650-675</td>
<td>14</td>
<td>14</td>
</tr>
<tr>
<td>675-700</td>
<td>12</td>
<td>9</td>
</tr>
<tr>
<td>700-725</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>&gt;725</td>
<td>11</td>
<td>9</td>
</tr>
<tr>
<td>Home damage and insurance:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Damage fraction (repair cost ÷ replacement cost)</td>
<td>.39 (sd=.32)</td>
<td>.58 (sd=.21)</td>
</tr>
<tr>
<td>Insurance fraction (insurance ÷ replacement cost)</td>
<td>.23 (sd=.21)</td>
<td>.30 (sd=.22)</td>
</tr>
<tr>
<td>Importance of Road Home grant formula discontinuity:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Damage fraction within 2 pct. pts. of RD threshold</td>
<td>4.4</td>
<td>6.6</td>
</tr>
<tr>
<td>Road Home participation:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nonparticipant</td>
<td>49</td>
<td>36</td>
</tr>
<tr>
<td>Rebuilding grant (option 1)</td>
<td>44</td>
<td>55</td>
</tr>
<tr>
<td>Relocation grant (option 2 or 3)</td>
<td>6</td>
<td>9</td>
</tr>
<tr>
<td>Home repaired by the pre-Katrina owner by year:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Immediately after Katrina</td>
<td>33</td>
<td>0</td>
</tr>
<tr>
<td>1 year after Katrina</td>
<td>42</td>
<td>13</td>
</tr>
<tr>
<td>2 years after Katrina</td>
<td>47</td>
<td>21</td>
</tr>
<tr>
<td>3 years after Katrina</td>
<td>52</td>
<td>29</td>
</tr>
<tr>
<td>4 years after Katrina</td>
<td>65</td>
<td>47</td>
</tr>
<tr>
<td>5 years after Katrina</td>
<td>70</td>
<td>54</td>
</tr>
<tr>
<td>Observations:</td>
<td>60,175</td>
<td>40,291</td>
</tr>
</tbody>
</table>

Note: This table reports summary statistics at the household level for the dataset analyzed in this paper. The sample includes all homes that were owner occupied in 2005, and located in Census blocks that contained at least five owner occupied homes in 2005. Source: Merged Orleans Parish Assessors Office property records and Louisiana Road Home administrative program microdata linked to block/tract/neighorhood background data from FEMA, and the 2000 Decennial Census.
Table 2: Descriptive Statistics, Census Blocks

<table>
<thead>
<tr>
<th>Variable</th>
<th>All blocks Mean (S.D.)</th>
<th>Blocks with any initially damaged homes Mean (S.D.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Demographic composition:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of households</td>
<td>12.6 ( 7.7)</td>
<td>12.9 ( 7.9)</td>
</tr>
<tr>
<td>Percent black (Census block)</td>
<td>61.7 (48.6)</td>
<td>69.0 (46.3)</td>
</tr>
<tr>
<td>Percent college educated (Census tract)</td>
<td>45.1 (49.8)</td>
<td>40.9 (49.2)</td>
</tr>
<tr>
<td>Pre-Katrina block flood exposure:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt; 2 feet</td>
<td>46.4 (49.9)</td>
<td>29.2 (45.5)</td>
</tr>
<tr>
<td>2 - 3 feet</td>
<td>12.8 (33.5)</td>
<td>17.0 (37.5)</td>
</tr>
<tr>
<td>3 - 4 feet</td>
<td>10.3 (30.5)</td>
<td>13.7 (34.4)</td>
</tr>
<tr>
<td>4 - 5 feet</td>
<td>9.9 (29.8)</td>
<td>13.1 (33.7)</td>
</tr>
<tr>
<td>5 - 6 feet</td>
<td>6.8 (25.2)</td>
<td>9.0 (28.7)</td>
</tr>
<tr>
<td>&gt; 6 feet</td>
<td>13.7 (34.4)</td>
<td>18.1 (38.5)</td>
</tr>
<tr>
<td>Equifax risk score (spatial moving average):</td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;600</td>
<td>23.8 (42.6)</td>
<td>25.8 (43.8)</td>
</tr>
<tr>
<td>600-625</td>
<td>18.0 (38.4)</td>
<td>19.6 (39.7)</td>
</tr>
<tr>
<td>625-650</td>
<td>16.4 (37.0)</td>
<td>16.1 (36.8)</td>
</tr>
<tr>
<td>650-675</td>
<td>12.4 (32.9)</td>
<td>11.7 (32.2)</td>
</tr>
<tr>
<td>675-700</td>
<td>10.9 (31.2)</td>
<td>8.7 (28.2)</td>
</tr>
<tr>
<td>700-725</td>
<td>9.0 (28.6)</td>
<td>8.6 (28.1)</td>
</tr>
<tr>
<td>&gt;725</td>
<td>9.5 (29.4)</td>
<td>9.4 (29.2)</td>
</tr>
<tr>
<td>Home damage and insurance:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Damage fraction (repair cost ÷ replacement cost)</td>
<td>0.38 (0.29)</td>
<td>0.50 (0.22)</td>
</tr>
<tr>
<td>Insurance fraction (insurance ÷ replacement cost)</td>
<td>0.22 (0.15)</td>
<td>0.26 (0.14)</td>
</tr>
<tr>
<td>Importance of Road Home grant formula discontinuity:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Any HHs with damage fraction within 2 pct. pts. of RD threshold</td>
<td>28.2 (45.0)</td>
<td>37.3 (48.4)</td>
</tr>
<tr>
<td># of HHs with damage fraction within 2 pct. pts. of RD threshold</td>
<td>0.56 (1.28)</td>
<td>0.74 (1.43)</td>
</tr>
<tr>
<td>Road Home participation:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nonparticipant</td>
<td>50.3 (30.6)</td>
<td>40.0 (26.2)</td>
</tr>
<tr>
<td>Rebuilding grant (option 1)</td>
<td>43.4 (27.1)</td>
<td>51.7 (23.8)</td>
</tr>
<tr>
<td>Relocation grant (option 2 or 3)</td>
<td>6.3 (11.1)</td>
<td>8.2 (12.1)</td>
</tr>
<tr>
<td>Home repaired by the pre-Katrina owner by year:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Immediately after Katrina</td>
<td>34.3 (43.4)</td>
<td>13.0 (25.4)</td>
</tr>
<tr>
<td>1 year after Katrina</td>
<td>44.9 (45.2)</td>
<td>27.1 (37.5)</td>
</tr>
<tr>
<td>2 years after Katrina</td>
<td>50.3 (43.8)</td>
<td>34.2 (38.5)</td>
</tr>
<tr>
<td>3 years after Katrina</td>
<td>55.3 (41.7)</td>
<td>40.8 (38.0)</td>
</tr>
<tr>
<td>4 years after Katrina</td>
<td>66.4 (32.9)</td>
<td>55.6 (30.8)</td>
</tr>
<tr>
<td>5 years after Katrina</td>
<td>70.9 (29.4)</td>
<td>61.5 (27.9)</td>
</tr>
<tr>
<td>Observations:</td>
<td>4,795</td>
<td>3,622</td>
</tr>
</tbody>
</table>

Note: This table reports summary statistics at the Census block level for the dataset analyzed in this paper. The sample used to compute the first column includes all Census blocks that contained at least five owner occupied homes in 2005. The second column excludes blocks with no initially damaged homes. The reported statistics are for the homes on those blocks that were owner occupied in 2005. Source: Merged Orleans Parish Assessors Office property records and Louisiana Road Home administrative program microdata linked to block/tract/neighborhood background data from FEMA, and the 2000 Decennial Census.
Table 3: Balance of Predetermined Covariates Above and Below the 51% Home Damage

<table>
<thead>
<tr>
<th></th>
<th>limit as (repair cost) ÷ (replacement cost)</th>
<th>limit as (repair cost) ÷ (replacement cost)</th>
<th>p-value of difference between (1) and (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>&gt; 51%</td>
<td>&gt; 51%</td>
<td>(3)</td>
</tr>
<tr>
<td>Fraction of homes undamaged (Census block):</td>
<td>0.048 (0.004)</td>
<td>0.046 (0.004)</td>
<td>0.698</td>
</tr>
<tr>
<td>Fraction black (Census block):</td>
<td>0.713 (0.011)</td>
<td>0.717 (0.01)</td>
<td>0.768</td>
</tr>
<tr>
<td>Fraction college (Census block group)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fraction college</td>
<td>0.474 (0.005)</td>
<td>0.480 (0.005)</td>
<td>0.342</td>
</tr>
<tr>
<td>Fraction college &lt; 10th city-wide pctile</td>
<td>0.088 (0.009)</td>
<td>0.098 (0.008)</td>
<td>0.373</td>
</tr>
<tr>
<td>Fraction college &lt; 25th city-wide pctile</td>
<td>0.215 (0.012)</td>
<td>0.213 (0.011)</td>
<td>0.910</td>
</tr>
<tr>
<td>Fraction college &lt; 50th city-wide pctile</td>
<td>0.491 (0.015)</td>
<td>0.484 (0.013)</td>
<td>0.729</td>
</tr>
<tr>
<td>Fraction college &lt; 75th city-wide pctile</td>
<td>0.845 (0.013)</td>
<td>0.816 (0.012)</td>
<td>0.094</td>
</tr>
<tr>
<td>Fraction college &lt; 90th city-wide pctile</td>
<td>0.943 (0.009)</td>
<td>0.946 (0.008)</td>
<td>0.778</td>
</tr>
<tr>
<td>Poverty rate (Census tract):</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poverty rate</td>
<td>0.198 (0.003)</td>
<td>0.200 (0.003)</td>
<td>0.774</td>
</tr>
<tr>
<td>Poverty &lt; 10th city-wide pctile</td>
<td>0.052 (0.009)</td>
<td>0.054 (0.008)</td>
<td>0.875</td>
</tr>
<tr>
<td>Poverty &lt; 25th city-wide pctile</td>
<td>0.194 (0.013)</td>
<td>0.194 (0.011)</td>
<td>0.979</td>
</tr>
<tr>
<td>Poverty &lt; 50th city-wide pctile</td>
<td>0.522 (0.015)</td>
<td>0.523 (0.014)</td>
<td>0.974</td>
</tr>
<tr>
<td>Poverty &lt; 75th city-wide pctile</td>
<td>0.788 (0.012)</td>
<td>0.790 (0.011)</td>
<td>0.916</td>
</tr>
<tr>
<td>Poverty &lt; 90th city-wide pctile</td>
<td>0.924 (0.009)</td>
<td>0.909 (0.008)</td>
<td>0.192</td>
</tr>
<tr>
<td>Equifax risk score (neighborhood s.m.a.):</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average risk score</td>
<td>636.7 (1.4)</td>
<td>638.4 (1.4)</td>
<td>0.425</td>
</tr>
<tr>
<td>Average risk score &lt; 10th city-wide pctile</td>
<td>0.103 (0.009)</td>
<td>0.119 (0.008)</td>
<td>0.177</td>
</tr>
<tr>
<td>Average risk score &lt; 25th city-wide pctile</td>
<td>0.260 (0.013)</td>
<td>0.260 (0.012)</td>
<td>0.992</td>
</tr>
<tr>
<td>Average risk score &lt; 50th city-wide pctile</td>
<td>0.567 (0.015)</td>
<td>0.535 (0.013)</td>
<td>0.116</td>
</tr>
<tr>
<td>Average risk score &lt; 75th city-wide pctile</td>
<td>0.830 (0.013)</td>
<td>0.831 (0.011)</td>
<td>0.929</td>
</tr>
<tr>
<td>Average risk score &lt; 90th city-wide pctile</td>
<td>0.958 (0.009)</td>
<td>0.949 (0.008)</td>
<td>0.462</td>
</tr>
<tr>
<td>Flooding (Census tract):</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Flood depth</td>
<td>3.14 (0.06)</td>
<td>3.17 (0.05)</td>
<td>0.753</td>
</tr>
<tr>
<td>Flooding &lt; 2 feet</td>
<td>0.293 (0.012)</td>
<td>0.288 (0.011)</td>
<td>0.772</td>
</tr>
<tr>
<td>Flooding 2-4 feet</td>
<td>0.409 (0.014)</td>
<td>0.411 (0.013)</td>
<td>0.910</td>
</tr>
<tr>
<td>Flooding 4-6 feet</td>
<td>0.222 (0.012)</td>
<td>0.229 (0.011)</td>
<td>0.676</td>
</tr>
<tr>
<td>Flooding &gt; 6 feet</td>
<td>0.077 (0.010)</td>
<td>0.072 (0.009)</td>
<td>0.729</td>
</tr>
<tr>
<td>Propensity score: pr( rebuild by t=5</td>
<td>Z_j )</td>
<td>0.576 (0.003)</td>
<td>0.580 (0.003)</td>
</tr>
<tr>
<td>Same-block neighbors' circumstances:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Avg. neighbors' damage fraction</td>
<td>0.535 (0.004)</td>
<td>0.528 (0.003)</td>
<td>0.180</td>
</tr>
<tr>
<td>Frac. of neighbors with &gt;51% damage</td>
<td>0.624 (0.008)</td>
<td>0.616 (0.007)</td>
<td>0.451</td>
</tr>
</tbody>
</table>

Note: Columns (1) and (2) report the average values of background variables among households with appraised home damage fractions (repair cost ÷ replacement cost) just above 51% versus just below 51%, the threshold at which RH grant offers increased discontinuously. Column (3) reports the p-value associated with the null that the two are equal. Source: Merged Orleans Parish Assessors Office property records and Louisiana Road Home administrative program microdata linked to block/tract/neighborhood background data from FEMA, and the 2000 Decennial Census.
Table 4: Structural Parameter Estimates

<table>
<thead>
<tr>
<th>Parameter:</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Spillover function: $S \times \text{BetaCDF}(\mu; \lambda_1, \lambda_2)$</strong></td>
<td></td>
</tr>
<tr>
<td>$S$: Spillover magnitude</td>
<td>0.43 [0.008]</td>
</tr>
<tr>
<td>$\lambda_1$: Location of spillover threshold</td>
<td>0.82 [0.003]</td>
</tr>
<tr>
<td>$\lambda_2$: Steepness of spillover nonlinearity</td>
<td>6.99 [0.401]</td>
</tr>
<tr>
<td><strong>Year-specific intercepts</strong></td>
<td></td>
</tr>
<tr>
<td>Year 1</td>
<td>-1.39 [0.048]</td>
</tr>
<tr>
<td>Year 2</td>
<td>-0.98 [0.027]</td>
</tr>
<tr>
<td>Year 3</td>
<td>-0.65 [0.031]</td>
</tr>
<tr>
<td>Year 4</td>
<td>-0.31 [0.030]</td>
</tr>
<tr>
<td>Year 5+</td>
<td>0.08 [0.018]</td>
</tr>
<tr>
<td><strong>Observable heterogeneity in flow location payoffs: $Z'y$</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Flood exposure:</strong></td>
<td></td>
</tr>
<tr>
<td>&lt; 2 feet</td>
<td>-0.22 [0.007]</td>
</tr>
<tr>
<td>2-3 feet (reference)</td>
<td>---</td>
</tr>
<tr>
<td>3-4 feet</td>
<td>0.07 [0.046]</td>
</tr>
<tr>
<td>4-5 feet</td>
<td>-0.14 [0.013]</td>
</tr>
<tr>
<td>5-6 feet</td>
<td>-0.18 [0.059]</td>
</tr>
<tr>
<td>&gt; 6 feet</td>
<td>-0.08 [0.058]</td>
</tr>
<tr>
<td><strong>Unobserved heterogeneity in flow location payoffs:</strong></td>
<td></td>
</tr>
<tr>
<td>$\sigma_\eta$: Variance of idiosyncratic attachment to pre-Katrina block</td>
<td>0.60 [0.035]</td>
</tr>
<tr>
<td>$\sigma_b$: Variance of unobserved block effect</td>
<td>0.39 [0.028]</td>
</tr>
<tr>
<td><strong>Credit Access:</strong></td>
<td></td>
</tr>
<tr>
<td>Cuttoff Credit Score for Rebuilding Loans ($\rho^*$)</td>
<td>678.5 [8.70]</td>
</tr>
</tbody>
</table>

| Observations - household-periods | 300,875 |
| Observations - households | 60,175 |

Note: This table reports estimates of the equilibrium rebuilding model’s structural parameters. Estimation is by indirect inference. Standard errors are computed by applying the delta method to the (clustered at the Census block level) standard errors of the underlying target auxiliary model parameters. Source: Authors’ calculations using Orleans Parish Assessor’s Office administrative property data linked with administrative application/participation data from the Louisiana Road Home program.
Table 5: The Road Home Program’s Partial-Equilibrium and Equilibrium Effects on Rebuilding

<table>
<thead>
<tr>
<th>Subgroup</th>
<th>(1) Rebuilding Rate</th>
<th>(2) Partial Equilibrium Road Home</th>
<th>(3) Equilibrium Road Home</th>
<th>(4) Spillover Multiplier</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>61.7</td>
<td>+6.3</td>
<td>+8.0</td>
<td>1.27</td>
</tr>
<tr>
<td>Flood depth:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt; 2 feet</td>
<td>76.2</td>
<td>+4.0</td>
<td>+4.5</td>
<td>1.13</td>
</tr>
<tr>
<td>2-3 feet</td>
<td>59.7</td>
<td>+10.5</td>
<td>+14.1</td>
<td>1.34</td>
</tr>
<tr>
<td>3-4 feet</td>
<td>59.5</td>
<td>+7.9</td>
<td>+11.2</td>
<td>1.42</td>
</tr>
<tr>
<td>4-5 feet</td>
<td>46.2</td>
<td>+9.4</td>
<td>+12.6</td>
<td>1.34</td>
</tr>
<tr>
<td>5-6 feet</td>
<td>35.6</td>
<td>+7.6</td>
<td>+9.3</td>
<td>1.22</td>
</tr>
<tr>
<td>&gt;6 feet</td>
<td>42.4</td>
<td>+6.3</td>
<td>+8.0</td>
<td>1.27</td>
</tr>
<tr>
<td>Rebuilding Rate w/o RH:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>90-100%</td>
<td>99.3</td>
<td>+0.1</td>
<td>+0.2</td>
<td>2.00</td>
</tr>
<tr>
<td>80-90%</td>
<td>85.1</td>
<td>+3.5</td>
<td>+5.3</td>
<td>1.51</td>
</tr>
<tr>
<td>70-80%</td>
<td>75.6</td>
<td>+5.5</td>
<td>+8.8</td>
<td>1.60</td>
</tr>
<tr>
<td>60-70%</td>
<td>66.0</td>
<td>+7.4</td>
<td>+11.0</td>
<td>1.49</td>
</tr>
<tr>
<td>50-60%</td>
<td>55.1</td>
<td>+8.0</td>
<td>+11.2</td>
<td>1.40</td>
</tr>
<tr>
<td>40-50%</td>
<td>45.4</td>
<td>+9.0</td>
<td>+11.8</td>
<td>1.31</td>
</tr>
<tr>
<td>30-40%</td>
<td>36.7</td>
<td>+9.7</td>
<td>+11.7</td>
<td>1.21</td>
</tr>
<tr>
<td>20-30%</td>
<td>26.2</td>
<td>+10.3</td>
<td>+11.9</td>
<td>1.16</td>
</tr>
<tr>
<td>10-20%</td>
<td>16.6</td>
<td>+13.4</td>
<td>+14.7</td>
<td>1.10</td>
</tr>
<tr>
<td>0-10%</td>
<td>4.7</td>
<td>+14.7</td>
<td>+14.9</td>
<td>1.01</td>
</tr>
</tbody>
</table>

Note: This table reports the results of simulation experiments.... Source: Authors’ calculations using the estimated equilibrium model.
Table 6: Decomposing the Welfare Effects of the Road Home Program’s Rebuilding Stipulations

<table>
<thead>
<tr>
<th>Group</th>
<th>% Marginal</th>
<th>Inframarginal Households ($)</th>
<th>Marginal Households ($)</th>
<th>Total ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>9.1</td>
<td>4,950</td>
<td>-24,360</td>
<td>2,177</td>
</tr>
<tr>
<td>&lt; 2 feet</td>
<td>4.8</td>
<td>1,954</td>
<td>-35,050</td>
<td>140</td>
</tr>
<tr>
<td>2-3 feet</td>
<td>15.7</td>
<td>12,890</td>
<td>-19,170</td>
<td>7,726</td>
</tr>
<tr>
<td>3-4 feet</td>
<td>13.4</td>
<td>10,010</td>
<td>-18,350</td>
<td>6,133</td>
</tr>
<tr>
<td>4-5 feet</td>
<td>14.8</td>
<td>7,384</td>
<td>-21,300</td>
<td>2,988</td>
</tr>
<tr>
<td>5-6 feet</td>
<td>11.0</td>
<td>2,894</td>
<td>-26,570</td>
<td>-475</td>
</tr>
<tr>
<td>&gt; 6 feet</td>
<td>9.7</td>
<td>4,453</td>
<td>-23,240</td>
<td>1,656</td>
</tr>
</tbody>
</table>

Note: This table reports the impact of the Louisiana Road Home program on average household welfare relative to an unconditional grant policy. RH required households who accepted “relocation” grants to turn their properties over to a state land trust, while the unconditional grant policy pays RH “rebuilding” grants to all households regardless of their rebuilding choices. RH offering smaller net grant packages to households who do not rebuild affects welfare through three channels: (1) changes to equilibrium property values, (2) changes to the non-pecuniary utility households derive from their equilibrium location choices (measured as equivalent variations), and (3) reductions to the size of net grant packages (for inframarginal non-rebuilding households). Because item (3) is an equal-sized benefit to the government, the total change to social welfare is the sum of (1) and (2). Source: Authors’ calculations using the estimated equilibrium model.
### Table 7: The Welfare Consequences of Alternative Policies

<table>
<thead>
<tr>
<th>Policy</th>
<th>(1) Per capita Aggregate</th>
<th>(2) Per capita Aggregate</th>
<th>(3) Aggregate Per capita</th>
<th>(4) Aggregate Aggregate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Govt. Savings</td>
<td>Δ HH Welfare</td>
<td>Δ Tot. Welfare</td>
<td>Δ Tot. Welfare</td>
</tr>
<tr>
<td>Unconditional grants [reference policy]</td>
<td>$0</td>
<td>$0</td>
<td>$0</td>
<td>$0</td>
</tr>
<tr>
<td>Category-specific welfare-maximizing ρ*:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>City is one category (uniform policy)</td>
<td>$9,593</td>
<td>-$6,945</td>
<td>$2,648</td>
<td>+$159M</td>
</tr>
<tr>
<td>Categories based on block demographics</td>
<td>$9,555</td>
<td>-$6,618</td>
<td>$2,936</td>
<td>+$177M</td>
</tr>
<tr>
<td>Categories based on t=0 damage-%</td>
<td>$9,111</td>
<td>-$6,022</td>
<td>$3,090</td>
<td>+$186M</td>
</tr>
<tr>
<td>Categories based on flood depth</td>
<td>$8,342</td>
<td>-$4,731</td>
<td>$3,611</td>
<td>+$217M</td>
</tr>
<tr>
<td>Categories based on t=0 damage-%, and flood depth interactions</td>
<td>$7,047</td>
<td>-$2,980</td>
<td>$4,066</td>
<td>+$244M</td>
</tr>
<tr>
<td>Perfect block-level targeting</td>
<td>$3,951</td>
<td>$2,048</td>
<td>$6,000</td>
<td>+$361M</td>
</tr>
</tbody>
</table>

Note: This table summarizes the results of counterfactual experiments comparing average household welfare under policies that offer smaller grants to households who do not rebuild to average welfare under a policy that pays RH rebuilding grants unconditionally. Specifically, we consider policies that offer a fraction \((1 - \rho)\) of the RH rebuilding grant to households if they choose to relocate, where \(\rho\) is chosen optimally subject to various constraints. The constraints we consider include: (1) that \(\rho\) be uniform city-wide, (2) that \(\rho\) be uniform within flood depth categories, (3) that \(\rho\) be uniform within baseline-block-rebuilding-rate categories, and (4) that \(\rho\) may be household-specific. Source: Authors’ calculations using the estimated equilibrium model.
Figure 1: Sketch of Equilibrium and the Possibility of “Tipping”

Note: This figure provides a stylized illustration of equilibria in our equilibrium model. Both panels plot hypothetical private demand schedules for rebuilding evaluated at the amenity level associated with a 0% rebuilding rate as well as actual marginal benefit curves. The private demand curve is downward sloping by definition as it is simply a highest-to-lowest ordering of individual households’ net benefits to rebuilding. The actual marginal benefit curve incorporates each additional household’s positive contribution to block amenities and can thus be downward or upward sloping. Self-consistent rebuilding rates are the zeros of the latter curve. The bottom panel illustrates how “tipping” can occur if a subsidy causes additional higher rebuilding rates to become self-consistent.
Figure 2: Parameterization of the Amenity Spillover Function

(a) Amplitude: $S^{(3)} > S^{(2)} > S^{(1)}$
(b) Shape: $\lambda_2^{(3)} > \lambda_2^{(2)} > \lambda_2^{(1)}$
(c) Location $\lambda_1^{(3)} > \lambda_1^{(2)} > \lambda_1^{(1)}$

Note: The amenity spillover function is given by $g(\mu) = S \cdot \text{BetaCDF}(\mu; \lambda_1, \lambda_2) : [0, 1] \rightarrow [0, S]$. Panel (a) shows how the parameter $S$ governs the function’s amplitude (with $\lambda_1, \lambda_2$ held fixed). Panel (b) shows how the parameter $\lambda_2$ governs the function’s shape (with $S, \lambda_1$ held fixed). Panel (c) shows how the parameter $\lambda_1$ governs the location of the strongest marginal spillovers (with $S, \lambda_2$ held fixed).

Figure 3: Households’ Financial Incentives and Rebuilding Choices by Appraised Home Damage Fraction

(a) Discontinuity = 19.6 (1.0)***
(b) Discontinuity = 0.050 (0.020)**

Note: The left panel of this figure shows the average opportunity cost of relocating instead of rebuilding within narrow home-damage-fraction bins. The opportunity cost of relocating instead of rebuilding was the smaller of a household’s RH rebuilding grant offer (which the household passed up if it sold its home privately) and its home’s as-is value (which the household had to turn over to the state if it accepted a RH relocation grant). The right panel shows the average rebuilding rate 5 years after Katrina within narrow home-damage-fraction bins. Source: Authors’ calculations using Orleans Parish Assessor’s Office administrative property data linked with administrative application/participation data from the Louisiana Road Home program.
Figure 4: Distribution of Appraised Home Damage Fractions

Note: Panel (a) of this figure plots the density of RH-appraised home damage fractions (repair cost ÷ replacement cost) close to the 51% RH grant threshold once all appeals of initial appraisals had been adjudicated. Panel (b) plots the density of initial RH-appraised home damage fractions close to the 51% grant-offer threshold. Panel (c) shows the full distribution of RH-appraised damage fractions. Source: Administrative application/participation data from the Louisiana Road Home program.
Figure 5: Difference Above vs. Below 51% Home Damage in the Rebuilding Rate of Close-by Neighbors

Note: This figure shows the difference between the rebuilding rates of neighbors households with just above versus just below 51% home damage (repair cost ÷ replacement cost) by distance from the home. Specifically the figure plots the estimated values of $\Delta^{(d)}$ from Equation (5) for $d = 0, ..., 1$. Source: Authors' calculations using Orleans Parish Assessor’s Office administrative property data linked with administrative application/participation data from the Louisiana Road Home program.
Figure 6: Difference Above vs. Below 51% Home Damage in the Distribution of Same-Block-Neighbor Rebuilding Rates

(a) Neighbors’ Rebuilding Rate by Home Damage Fraction

(b) Neighbors’ Rebuilding Rate CDF Above/Below Grant Threshold

Note: The top panel of this figure plots the average rebuilding rate of households’ same-Census-block neighbors within narrow home-damage-fraction (repair cost ÷ replacement cost) bins. The bottom panel shows the CDF of same-block-neighbor rebuilding rates for households with just above and just below 51% home damage. See the discussion of Equation (7) in the text for details about the estimation procedure. Source: Authors’ calculations using Orleans Parish Assessor’s Office administrative property data linked with administrative application/participation data from the Louisiana Road Home program.
Figure 7: Spillover Effects of Rebuilding on Flow Amenity Utility and Offered Home Prices

Note: The top panel of this figure plots the estimated shape of the equilibrium model’s amenity spillover function \( g(\mu) \). The bottom panel plots the estimated impact of same-block neighbors’ rebuilding on home price offers (specifically, the neighbors’ rebuilding rate spline from Equation (8)). Source: Authors’ calculations using Orleans Parish Assessor’s Office administrative property data linked with administrative application/participation data from the Louisiana Road Home program.
Private response to a larger private grant offer:

\[
Y_i \begin{cases} \text{Repair Dummy} \\ \text{Larger R.H. Grant} \end{cases} = \bar{y} + \Delta^{(y)} \times 1_{R_i > 0} + f(R_i; a_y) + e_i
\]

Spillover from larger private grant offer onto neighbors’ rebuilding:

\[
\mu_{j(i),-i} \begin{cases} \text{Neighbors’ Rebuilding Rate} \\ \text{Larger R.H. Grant} \end{cases} = \bar{\mu} + \Delta \times 1_{R_i > 0} + f(R_i; \bar{\pi}) + e_i
\]

Spillover from larger private grant offer onto neighbors’ rebuilding thresholds:

\[
1(\mu_{j(i),-i} > .1) = S^{(10)} + \Delta^{(10)} \times 1_{R_i > 0} + f(R_i; a_{10}) + e_i
\]
\[
1(\mu_{j(i),-i} > .2) = S^{(20)} + \Delta^{(20)} \times 1_{R_i > 0} + f(R_i; a_{20}) + e_i
\]
\[
\vdots
\]
\[
1(\mu_{j(i),-i} > .9) = S^{(90)} + \Delta^{(90)} \times 1_{R_i > 0} + f(R_i; a_{90}) + e_i
\]
Table A1: The Road Home Program’s Partial-Equilibrium and Equilibrium Effects on Rebuilding

<table>
<thead>
<tr>
<th>Subgroup</th>
<th>Baseline Model</th>
<th>Alternative Eqm.-Selection Rule</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>+8.0</td>
<td>+7.6</td>
</tr>
<tr>
<td>Flood depth:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt; 2 feet</td>
<td>+4.5</td>
<td>+4.4</td>
</tr>
<tr>
<td>2-3 feet</td>
<td>+14.1</td>
<td>+13.1</td>
</tr>
<tr>
<td>3-4 feet</td>
<td>+11.2</td>
<td>+10.5</td>
</tr>
<tr>
<td>4-5 feet</td>
<td>+12.6</td>
<td>+11.4</td>
</tr>
<tr>
<td>5-6 feet</td>
<td>+9.3</td>
<td>+8.8</td>
</tr>
<tr>
<td>&gt;6 feet</td>
<td>+8.0</td>
<td>+7.6</td>
</tr>
<tr>
<td>Rebuilding Rate w/o RH:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>90-100%</td>
<td>+0.2</td>
<td>+0.2</td>
</tr>
<tr>
<td>80-90%</td>
<td>+5.3</td>
<td>+5.0</td>
</tr>
<tr>
<td>70-80%</td>
<td>+8.8</td>
<td>+7.7</td>
</tr>
<tr>
<td>60-70%</td>
<td>+11.0</td>
<td>+9.9</td>
</tr>
<tr>
<td>50-60%</td>
<td>+11.2</td>
<td>+10.3</td>
</tr>
<tr>
<td>40-50%</td>
<td>+11.8</td>
<td>+11.4</td>
</tr>
<tr>
<td>30-40%</td>
<td>+11.7</td>
<td>+11.5</td>
</tr>
<tr>
<td>20-30%</td>
<td>+11.9</td>
<td>+11.1</td>
</tr>
<tr>
<td>10-20%</td>
<td>+14.7</td>
<td>+13.4</td>
</tr>
<tr>
<td>0-10%</td>
<td>+14.9</td>
<td>+12.7</td>
</tr>
</tbody>
</table>

Note: This table compares the simulated equilibrium impacts of the Road Home grant program on rebuilding rates using the baseline model (column 1), which assumes that the total-welfare-maximizing equilibrium is selected on blocks with multiple self-consistent equilibria, to the simulated impact of RH using a (re-estimated) version of the model that assumes the total-welfare-minimizing equilibrium occurs in such cases (column 2). Source: Authors’ calculations using the estimated equilibrium models.
Figure 9: Goodness of Fit: Trends in Fraction of Homes Livable by Neighborhood Characteristics

(a) All Blocks

(b) < 2 feet of flooding

(c) 2-3 feet of flooding

(d) 3-4 feet of flooding

(e) 4-5 feet of flooding

(f) 5-6 feet of flooding

(g) 6+ feet of flooding

(h) Avg. Score <600

(i) Avg. Score 600-625

(j) Avg. Score 625-650

(k) Avg. Score 650-675

(l) Avg. Score 675-700

(m) Avg. Score 700-725

(n) Avg. Score >725
Figure 10: Goodness of Fit: Histogram of 5th-Anniv. Block Repair Rates by Neighborhood Characteristics

(a) All Blocks

(b) < 2 feet of flooding

(c) 2-3 feet of flooding

(d) 3-4 feet of flooding

(e) 4-5 feet of flooding

(f) 5-6 feet of flooding

(g) 6+ feet of flooding

(h) Avg. Score <600

(i) Avg. Score 600-625

(j) Avg. Score 625-650

(k) Avg. Score 650-675

(l) Avg. Score 675-700

(m) Avg. Score 700-725

(n) Avg. Score >725
Note: This figure summarizes our estimated rules for optimally targeting relocation penalties at the block level. Considering a class of policies that offer the Road Home rebuilding grant to all households who rebuild and a fraction \((1 - \rho)\) of that grant to households who relocate, we calculated the optimal block-specific penalty \(\rho^*\) that maximize welfare on each block. We then regress the block-specific \(\rho^*\) values on block flood depth, the block damage rate, block percent black, block percent college-educated, and block average block Equifax risk scores. This figure’s contours summarize the predicted values from this regression evaluated at the city-wide average values of the race, education, and credit variables. Source: Authors’ calculations using the estimated equilibrium model.