TARGETING DISASTER AID: A STRUCTURAL EVALUATION OF A LARGE EARTHQUAKE RECONSTRUCTION PROGRAM

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This paper studies the question of how to target aid after a natural disaster. Disaster aid programs often use property damage as a criterion for eligibility. A household's ability to insure against shocks may be harder to observe but more important in determining how the disaster affects welfare. We develop a model of household demand for reconstruction aid and estimate the model parameters using data from a household survey following the 2015 Nepal earthquake and moments derived from a spatial regression discontinuity design. We use the model to estimate welfare from counterfactual targeting strategies. Conditioning aid on property damages increases welfare by 6% relative to a random allocation, but a geographically targeted aid strategy based on earthquake intensity would have increased welfare by more. We also show that policymakers face trade-offs between targeting strategies aimed at consumption smoothing and those prioritizing poor households. Notably, damage-based targeting proves ineffective in reaching poor households.

KEYWORDS: Natural Disasters, Targeting, Aid, Consumption Smoothing.

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1. INTRODUCTION

Cash transfers to households after a natural disaster could be an effective way to mitigate the negative impacts of the disaster and promote reconstruction, especially when households lack insurance or other means of smoothing the shock. A common approach to targeting aid in post-disaster reconstruction programs is to make eligibility conditional on disaster-related property damage. The relevance of using property damage as a proxy for need is not well established in economic theory or empirically, however. Other forms of vulnerability, including barriers to credit and insurance markets, are harder to observe, but important determinants of a household's post-disaster welfare and ability to recover.

This paper studies the question of how to target aid after a disaster, using the 2015 Nepal earthquake as a case study. The 2015 earthquake was the largest in Nepal since 1934, and by some estimates left 12% of the country homeless (The Asia Foundation, 2016*b*). In the months after the earthquake, households could qualify for a large cash grant based on the degree of damage to their house.

We analyze the welfare and reconstruction implications of this targeting policy and several alternatives by estimating a model of household behavior using a panel of rural households covering the reconstruction period. The model assumes that households can draw upon savings and informal insurance to smooth shocks, but they face a borrowing constraint. We build evidence for these assumptions by exploiting a spatial discontinuity in aid delivery. Regression discontinuity estimates show that aid increases consumption and housing investment, but decreases remittances – a common form of informal insurance. We use these estimates to calibrate the parameters of our structural model.

We then present a framework to measure the benefits of aid, taking into account different possible objectives. In the context of anti-poverty programs, targeting strategies are often evaluated according to a utilitarian social welfare function, which assesses how accurately the program directs aid to the households with the highest marginal value for cash (Niehaus et al., 2013, Hallegatte et al., 2016, Hanna and Karlan, 2017, Hanna and Olken, 2018, Aiken et al., 2022, Banerjee et al., 2023). We find that targeting based on property damages is not effective according to this metric – it generates just 52% of the welfare of a random allocation.

On the other hand, the objectives of disaster aid might be different – a planner might seek to help recipients recover from a shock, regardless of how well-off they were initially. We derive a measure of household 'demand for aid', that can be interpreted as a household's willingness-to-pay to smooth a shock. We measure demand as the amount of income a household would be willing to forgo in the future in exchange for receiving aid in the present. Demand for aid goes down when households have alternative means of insurance, and increases when liquidity constraints bind. This measure distinguishes a households' willingness-to-pay from their ability-to-pay, which can be relevant when households face credit market failures. The estimates of demand for aid derived from our structural model correlate with costly household coping strategies, such as taking on high-interest loans, migration, and children working.

According to this measure of welfare, the targeting strategy pursued in Nepal increased welfare by 5% relative to a random allocation of aid. Other strategies perform better as well, or better, however. A universal allocation, that gives a smaller amount of money to all households in the affected districts does just 1% worse than the true allocation, without accounting for administrative cost savings or delays. A strategy that targeted all households in villages with the highest measures of earthquake intensity would have performed 3% better than the actual allocation.

These alternatives perform well for two reasons. First, some households that experienced damages have 'insurance' – access to loans and remittances that allow them to recover regardless of whether they receive aid. Second, some households have no property damage, but have high value for aid in order to meet their immediate need for consumption.

We also explore 'reduced form' social welfare functions, that assume the planner wants to increase either aggregate consumption or housing reconstruction. This latter goal could be important if housing reconstruction has large externalities or general equilibrium effects. We find that, while damage based targeting does better than the random allocation in promoting reconstruction, it does worse than targeting low-wealth households.

These qualitative results are robust to alternate parameter estimates or assumptions about household income dynamics. We also explore how the optimal targeting policy depends on both average wealth and inequality. Targeting is more valuable as both wealth and inequality increase.

This paper contributes to the growing literature on targeting aid by developing a framework for studying the targeting of disaster aid. The existence of nepotism and politics in the distribution of disaster aid has been well documented (Basurto, Dupas and Robinson, 2020, Tarquinio, 2022, Mahadevan and Shenoy, 2023), including in the context of the Nepal earthquake (Bhusal et al., 2022, Pathak and Schündeln, 2022). We take a normative analysis, building off of the utilitarian framework common in the anti-poverty literature, to critically examine the objectives of disaster aid, and to show that even well-intentioned targeting strategies may be sub-optimal.

We adapt previous work using structural models to study the welfare implications of disaster aid, which to date has mainly focused on the US, and the Hurricane Katrina recovery in particular. Our model emphasizes rural income risk and the welfare gains from targeting, which are first order concerns in the design of social insurance in poor countries, whereas previous work has studied program design to minimize moral hazard and maximize rebuilding externalities – concerns that may be more important in an urban context in a wealthy country with more comprehensive social insurance programs (Gregory, 2017, Fu and Gregory, 2019).

In addition, we show empirical evidence on the causal effects of disaster aid on consumption, income, and investment in a low-income country using a spatial regression discontinuity approach. The research design relies on the fact that households in certain districts were prioritized for aid, and that households close to the borders of those districts experienced similar levels of earthquake damages, but differed in their likelihood of receiving aid. The results show that receipt of aid has large effects on household consumption and housing reconstruction. Aid also substituted for some types of informal insurance including remittances and migration. These effects are consistent with a model of partially insured households.

We also show evidence that there is considerable heterogeneity in households' ability to smooth consumption. The forms of insurance used in this context – mainly loans, remittances and migration – are not equally available to all households. In particular, wealthy households are less likely to experience damages from the disaster, but conditional on damages, they are also better able to recover by drawing on sources of informal insurance.

Heterogeneity in the ability to smooth shocks explains why the effects of disasters vary across contexts. Previous work finds that the negative effects of disasters on GDP is larger in poorer countries (see Kellenberg and Mobarak 2011; Dell, Jones and Olken 2014; and Botzen, Deschenes and Sanders 2019 for reviews). In the US, studies using administrative data often show transitory impacts on income for even very large disasters, though recovery is aided by reliance on insurance and formal social safety nets that may not be as robust in low-income countries (Deryugina, 2017, Deryugina, Kawano and Levitt, 2018, Gallagher and Hartley, 2017, Billings, Gallagher and Ricketts, 2022, Gallagher, Hartley and Rohlin, 2023). This heterogeneity could make targeting important. Tarquinio (2022) finds that drought declarations in India increase household consumption, but the effect is smaller when the declarations are poorly targeted.

Our results show substantial heterogeneity in household demand for aid, even between rural households in a low-income country. Earthquake-related housing damages contribute to this demand, but a targeting strategy exclusively focused on that proxy will miss households facing other types of vulnerabilities. If these vulnerabilities are not easily observable, geographic targeting, or giving a smaller amount of aid to a larger number of people may be simple policies that improve welfare.

The remainder of the paper is as follows. Section 2 provides context on the earthquake and the aid program, and shows descriptive evidence of the means by which households smooth consumption, as well as heterogeneity in access to informal insurance. Section 3 describes our normative framework, and presents a structural model enabling us to obtain estimates of household demand for aid. Section 4 estimates the model using the method of simulated moments, including moments derived from a spatial regression discontinuity in the allocation of aid. Section 5 then uses the model to analyze the implications of counterfactual targeting strategies on welfare and reconstruction.

2. CONTEXT AND DATA

With a 2015 per capita GDP of $3,330, Nepal ranks as one of the poorest countries in the world outside of Africa. Two-thirds of households are employed in agriculture or livestock rearing,[1] and the economy remains heavily dependent on migrant labor and remittances, which also provide an important means of insuring against environmental shocks.

[1] Data from World Bank. In 2015 exchange rates averaged close to 100 NPR to $1.

The Himalayan portion of the country is a subduction zone that experiences frequent earthquakes. In April 2015, the Gorkha earthquake, named after the district where it occurred, measured a 7.8 on the Richter scale – the largest earthquake in Nepal since 1934. The earthquake also triggered landslides throughout the region flattening entire villages. The final death toll was nearly 9,000 people, and an estimated 12% of the country had their homes destroyed (The Asia Foundation, 2016*b*).

The earthquake took place in a context of poor state capacity. Nepal endured a decade of Civil War from 1996-2006, followed by eight years of transitional governments in the lead-up to the earthquake. Riots and a blockade of the border with India, and a drought in 2016, compounded food insecurity in the aftermath of the disaster (Randell et al., 2021).

In the fourteen most severely affected districts, several small emergency cash grants were distributed within six months of the earthquake. Households that had their homes completely destroyed typically received 25,000 NPR (about $250) to buy emergency supplies and procure shelter before winter set in. Village Development Committee (VDC) leaders compiled initial lists of households eligible for benefits, with some discretion in their ability to do so (The Asia Foundation, 2016*b*, Pathak and Schündeln, 2022).

An initial needs assessment conducted after the earthquake identified rural housing reconstruction as the largest need area (Government of Nepal National Planning Commission, 2015). A multilateral donor fund pledged $4.1B for household grants to rebuild earthquake resilient houses, with the grants initially targeted at the fourteen most affected districts (Nepal Earthquake Housing Reconstruction Program Multi Donor Trust Fund, 2016).

Households qualified for reconstruction aid if their house required complete rebuilding, as certified by teams of engineers sent by the central government. This resulted in new beneficiary lists that were, in many cases, less generous than the initial lists, leading to more protests and unrest in some districts. Although some households had started repairs, The Asia Foundation (2016*a*) found that 75% of displaced households were still living in temporary shelters 18 months after the earthquake, with many more moving back into their partially reconstructed and potentially unsafe homes.

For households that qualified, the reconstruction grants amounted to 300,000 NPR ($3,000), delivered in three tranches. The first funds were delivered in early 2016, a full year after the earthquake. By July 2018, 60% of eligible households in the most-affected districts had received at least two installments, compared to only 15% of eligible house-

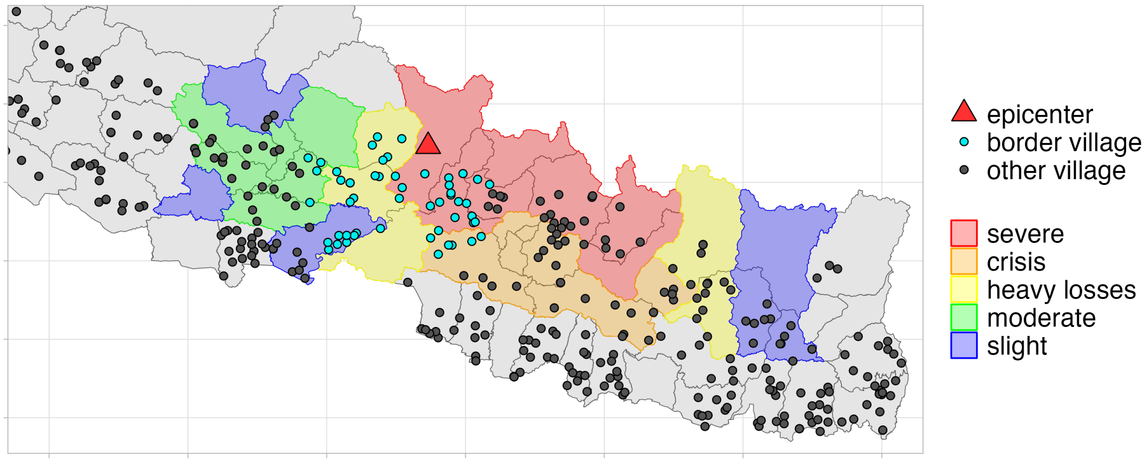

FIGURE 1.—Map of study region. District colors denote earthquake damage designations from Housing Recovery and Reconstruction Platform (2018). 'Severe' and 'Crisis' districts were prioritized for aid. Black circles represent VDCs present in the survey. Blue circles are VDCs within 59 km of the western border of the 'Severe' and 'Crisis' districts – the bandwidth selected for inference in the first stage of the regression discontinuity analysis (see Section 4.1).

holds outside those districts (Housing Recovery and Reconstruction Platform, 2018). These reconstruction grants are the focus of the targeting analysis in this paper.

Within villages, earthquake damages negatively correlated with income, assets, and education (see Appendix C). This seemed mainly to reflect wealthier households using better building materials, as cement and reinforced concrete buildings fared better on average. The aid response did not favor the poor, however. Bhusal et al. (2022) find that elite caste members received more aid, even after controlling for assessed damages. This bias was partially reversed in VDCs with mayors from non-elite castes, however.

2.1. *Data and Descriptive Statistics*

Our primary source of data is the World Bank Household Risk and Vulnerability Survey (WBHRVS) – a representative panel survey of 6,000 rural households from across Nepal that covers 2016-18, with one wave corresponding to each year in that time period (Walker, Kawasoe and Shrestha, 2019).[2] The survey collected data on household asset, livelihood,

[2]While migration of affected households could be a concern after a large natural disaster, barriers to international migration are high, and most migration is internal. Given the national representativeness of the survey, it should be representative of both earthquake affected and non-affected households.

and consumption variables, as well as shocks experienced and coping strategies. It also records whether households received earthquake reconstruction aid. The survey was conducted separately from the engineering assessments that determined household eligibility for aid. The locations of sample households are shown (Figure 1). We also use data from the US Geological Survey to measure slope, elevation, and peak ground acceleration during the earthquake. The latter is used to define a targeting strategy based on earthquake intensity. Finally, to look at the correlates of earthquake damages in Appendix C, we use the post-earthquake building census conducted by the National Reconstruction Authority.

Average income of the households in the sample is 275,000 NPR (Appendix Table B.I). Given an average household size of 4.66, this comes out to be approximately $1.60 per person per day. This goes up to nearly $2 when remittances are included. 10% of households report that they skipped a meal in the last 30 days. Long-term migration is an important livelihood strategy. Nearly half of the households in the sample are economically connected to a migrant, with many connected to more than one. More than half of the migrants mentioned by the households in the sample were in another country – with India, Southeast Asia, and the Middle East as the main destinations. Loans are important in this context as well, with the average household taking 29,000 NPR in short term loans in the past year. The most common source of loans is from friends and relatives (40%) with money lenders and savings groups accounting for most of the rest. Formal banking services account for a negligible fraction of loans.

Of the twenty-one percent of households that report experiencing losses from the earthquake, 97% of those report asset losses, compared to 22% reporting income losses – consistent with findings in the post-disaster needs assessment prioritizing housing as the main focus of reconstruction. In addition to the nature of the earthquake as a shock that primarily destroys fixed capital, another possible explanation for this distribution of losses is that many households' primary source of income comes from migrants overseas, which was unaffected by the earthquake. Thirteen percent of households received at least one installment of aid.

2.2. *Consumption Smoothing*

Targeting could increase the value of aid as a form of social-insurance if it is directed towards households that are least able to smooth consumption (Chetty, 2006). To test for heterogeneity in household ability to smooth consumption, we use Townsend-style regressions, regressing consumption on income conditional on household and village-year fixed effects (Townsend, 1994). This tests whether idiosyncratic income shocks correlate with household consumption. Results in Table I reject the null hypothesis of perfect risk sharing. For a 10% reduction in income, households reduce food consumption by 1% on average.

There is important heterogeneity across several subgroups in the sample, however. The second column explores heterogeneity by caste and ethnicity. Members of the economically and politically powerful Newar caste smooth consumption more effectively than other groups as indicated by the negative coefficient on the interaction term. This could be consistent with Bhusal et al. (2022) findings on preferential access to aid amongst the politically dominant caste. The last three columns show heterogeneity by sex of household head, value of landholdings, and earthquake exposure. Female headed households and households with above median landholdings smooth consumption more effectively.

Landownership is a proxy for wealth, and the results suggest that wealthier households are better insured. The negative coefficient on female-headed households might be somewhat surprising in the light of often presumed increased vulnerability amongst these households, however one potential explanation is that 61% percent of these households receive remittances, compared to 26% of male-headed households, and remittances tend to be strongly counter cyclical, as seen in Table II.A. Notably, earthquake exposed households seem to smooth no worse on average, though this combines the effect of the earthquake with the effect of the aid. These patterns of heterogeneity are similar with caste-year fixed effects instead of village-year fixed effects, or if we use rainfall as an instrument for income (Appendix Tables B.II and B.III).

To test which types of transfers are pro- or counter-cyclical with respect to household income fluctuations, we regress various types of transfers on log income, conditional on a household fixed effect. The columns in Table II.A show that remittances, migration, and loans negatively correlate with within-household income fluctuations, suggesting that they are used as forms of informal insurance. Cash savings are pro-cyclical, suggesting that

	log(consumption)				
	(1)	(2)	(3)	(4)	(5)
log(income)	0.103***	0.101***	0.102***	0.110***	0.101***
	(0.006)	(0.009)	(0.006)	(0.007)	(0.006)
log(income):Dalit		0.009			
		(0.014)			
log(income):Newar		−0.045**			
		(0.015)			
log(income):Other		0.005			
		(0.009)			
log(income):Female Head			−0.010***		
			(0.002)		
log(income):Land > Median				−0.013**	
				(0.006)	
log(income):Quake Affected					0.012
					(0.012)
Observations	16 742	16 741	16 742	16 742	16 742
R2	0.792	0.792	0.793	0.792	0.792

TABLE I

CONSUMPTION SMOOTHING

All regressions include household and village-year fixed effects. Standard errors clustered at the survey strata. Observations with zero or missing income, or less than 3 observations dropped. Land percentile defined based on household land value during first survey wave. Omitted category for caste is "Brahmin/Chhetri". * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

households save in a good year and draw on savings in bad years. Earthquake aid is positively correlated with income shocks, possibly because it arrived more than a year after the event in most cases. Government transfers are also pro-cyclical, highlighting the absence of formal social insurance that responds to shocks.

To test how various forms of transfers correlate with wealth, we regress various forms of transfer income on a dummy for above median landholdings, conditional on a village-year fixed effect that captures aggregate shocks to the village. Table II.B shows that cash savings, remittances, migration, and loans in a given year are positively correlated with household landholdings within villages, suggesting that these sources of support are more easily available to wealthier households.

Taken together these correlations indicate that households vary in their ability to smooth income shocks, possibly due to differential access to savings, loans, remittances and mi-

A. Within Household Variation

	Earthquake Aid (1)	NGO Transfers (2)	Govt Transfers (3)	Informal Transfers (4)	Cash Savings (5)	Remittances (6)	Migrants (7)	Loans Taken (8)
log(income)	2.370*	−0.222	0.001***	0.268	7.606***	−8.678***	−0.051***	−3.557*
	(1.174)	(0.206)	(0.000)	(0.191)	(1.884)	(1.660)	(0.012)	(1.767)
Observations	16742	16742	16742	16739	16671	16742	16742	16728
R2	0.493	0.333	0.650	0.342	0.505	0.604	0.375	0.361
Fixed Effects	Household	Household	Household	Household	Household	Household	Household	Household

B. Within Village-Year Variation

	Earthquake Aid (1)	NGO Transfers (2)	Govt Transfers (3)	Informal Transfers (4)	Cash Savings (5)	Remittances (6)	Migrants (7)	Loans Taken (8)
Land > Median	−0.007	−0.103	0.001	−0.172	34.231***	21.307**	0.042**	4.052*
	(0.349)	(0.179)	(0.000)	(0.728)	(3.009)	(7.287)	(0.015)	(1.909)
Observations	16742	16742	16742	16739	16671	16742	16742	16728
R2	0.488	0.362	0.121	0.078	0.141	0.140	0.142	0.110
Fixed Effects	Village-Year	Village-Year	Village-Year	Village-Year	Village-Year	Village-Year	Village-Year	Village-Year

TABLE II

TRANSFER INCOME

Panel A shows labor income regressed on various forms of transfer income and a migration dummy conditional on a household fixed effect. Panel B shows the results of a regression of forms of transfer income and a migration on dummy on an indicator for land value greater than median in the first survey wave conditional on a village-year fixed effect. All dependent variables except migration in thousands of NPR. Households with zero or missing income or less than 3 observations dropped. Standard errors clustered at the survey strata. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

gration opportunities. This implies that aid might have greater benefits if targeted towards households that lack these forms of informal insurance. In the next section, we present a model of household behavior and a normative framework based on these results.

3. TARGETING CRITERIA FOR RECONSTRUCTION AID

Judging the merits of different allocations of aid inherently requires making interpersonal comparisons between households – assuming the planner has a fixed budget means that giving aid to one household requires not giving it to another. Consider a social welfare function that aggregates the indirect utility functions of households indexed by i according to:

$$W = \sum_{i=0}^{N} \alpha_i V_{it}(a_{it}, x_{it}, h_{it}, P_{it}) \tag{1}$$

$$\text{such that } \sum_{i=0}^{N} a_{it} \leq A$$

V_{it} is the indirect utility function of household i at time t that depends on aid received (a_{it}), and other sources of heterogeneity between households. These include the quality of their housing stock, reflecting damage from the earthquake (h_{it}), access to liquidity for reconstruction (x_{it}), and permanent income (P_{it}). Ability to access liquid wealth is a particularly important determinant of self-insurance for a large covariate shock in a developing country where informal networks form an important risk sharing mechanism (Munshi and Rosenzweig, 2016, Morten, 2019). Each household has Pareto-weight α_i, which the planner chooses based on targeting objectives. A is the aid budget.

Much of the targeting literature focused on poverty alleviation has used a utilitarian social welfare function to assess benefits, where all households have $\alpha_i = 1$. Given a concave value function, this functional form favors redistribution to the poorest households. While this is probably appropriate for analyzing poverty-relief programs, it may not fit the goals of disaster-reconstruction aid as well. A utilitarian planner would only condition aid on disaster-related damages if those damages were a good proxy for a high marginal utility of aid. We will analyze to what extent this is true in our setting, but we also examine social welfare functions that reflect other objectives.

In particular, we also consider a social welfare function consistent with the idea that the purpose of disaster aid is to help households smooth consumption and maintain their quality-of-life in the aftermath of the disaster. Intuitively, this type of objective is more consistent with a targeting strategy based on disaster damages.

Typical analyses of the allocation of non-market goods seek to maximize willingness-to-pay – a metric that makes little conceptual sense when considering cash aid, since the nominal value of the aid is the same to all households. Instead, to implement an objective focused on consumption smoothing, we measure what percentage of future income a household would be willing to give up in exchange for the amount of aid disbursed by the reconstruction program. This value can be inferred by solving for a tax on future income, τ_i, such that a household is indifferent between their current liquidity and income, and receiving the aid, but paying a tax on future income:

$$V(x_{it}, h_{it}, P_{it}) = V(x_{it} + a_{it}, h_{it}, (1 - \tau_i)P_{it}). \tag{2}$$

This is the household's compensating variation for liquidity in terms of future income. A notion of the household's 'willingness-to-pay' (WTP) for aid can be calculated as a discounted sum of expected future tax payments, with discount factor β. In discrete time:

$$WTP_{it} = \sum_{t=0}^{\infty} \beta^t(\tau_i P_{it}) = \frac{\tau_i P_{it}}{1-\beta}. \tag{3}$$

Measuring demand for aid in this manner is like asking a household how much they would be willing to borrow from their future self in order to smooth the present shock. It is a useful concept in a context with credit market constraints, since if markets were complete, households could borrow at prevailing interest rates. With the borrowing constraint, however, households might be willing to pay above market interest rates (and be able to repay in expectation), but they are unable to find a lender willing to offer those terms. In this way, we can think of a concept of willingness-to-pay that is distinct from ability-to-pay.

This form of SWF satisfies some desirable theoretical properties, including an idealized form of inter-temporal Kaldor-Hicks efficiency. If households were allowed to make transfers through time, households that don't receive aid could be compensated with the future income of those that do to create a Pareto improvement.

This measure of demand-for-aid can be connected to our social welfare function, by observing that it prioritizes households that have the highest value of $\tau_i P_{it}$, defined as ΔP_{it}, since it represents a discrete change in expected household income. Defining $\frac{\Delta V}{\Delta A_i}$ and $\frac{\Delta V}{\Delta P_{it}}$ as the discrete analogs of the derivative of the value function with respect to aid and expected income, some algebraic manipulation from equation (2) shows that:

$$\frac{\frac{\Delta V}{\Delta A_i}}{\frac{\Delta V}{\Delta P_{it}}} = \frac{\Delta P_{it}}{\Delta A_i}. \tag{4}$$

Since the amount of the aid package is the same for all households, allocating aid to households with the highest ΔP_{it} is equivalent to allocating aid to households with the highest $\frac{\Delta V}{\Delta A_i} / \frac{\Delta V}{\Delta P_{it}}$. This is exactly the result that would occur from maximizing equation 1 with $\alpha_i = (\frac{\Delta V}{\Delta P_{it}})^{-1}$.

This is closely related to previous work on social welfare functions and non-market valuation. It is well known that maximizing a social welfare function weighted by the inverse marginal utility of income is equivalent to maximizing willingness-to-pay (Negishi, 1960). These 'Negishi weights' are often used in non-market valuations to separate distributional questions from questions of efficiency by replicating the market allocation that would occur under complete markets and freezing the distribution of income (Nordhaus and Yang, 1996). In the case of cash aid, however, since cash is fungible with income up to the interest rate, a Negishi weighted social welfare function will just return the market interest rate.

Therefore, instead of weighting by the inverse marginal utility of income, we weight by the inverse marginal utility of *expected future* income. This social welfare function can be seen as freezing the distribution of expected lifetime resources. In other words, the social planner is interested in helping households smooth temporary shocks, but not in redistributing long-run wealth.

Specifying welfare in this way may be regressive in that it gives higher weight to households with high-permanent incomes. On the other hand, wealthy households may be able to satisfy their reconstruction needs by drawing on their savings, or borrowing at a low interest rate. Households with little savings, informal insurance, or access to credit might be willing to pay more to meet their current needs.

Another important consideration is that our framework above uses P_{it} in the time period that the aid is delivered. In some sense this is natural, since it is what would be measured in a post-disaster needs assessment, and it is in fact the variable that we are able to measure in our data. Other possibilities exist, however. We could construct weights using pre-disaster permanent income, which would give a sense of the household's willingness-to-pay to avoid the disaster. On the other hand, we could use post-aid permanent income, which would be relevant if the aid allowed households to make investments that increased permanent income. In our setting, we find limited evidence of either the disaster or aid having large effects on incomes,[3] which is unsurprising since the major effects of both the earthquake and the aid program were on the housing stock rather than productive assets. Section 5.1 performs some sensitivity tests to these other measures of welfare, allowing

[3] See Appendix Table C.I for effects of the earthquake on income, and the regression discontinuity results in Section 4.1 for estimates of the effects of aid on income.

permanent income to change with disaster damages and/or the receipt of aid, but given our lack of pre-earthquake income data, we leave a more detailed examination of the quantitative differences between these measures to future work.

One potential objection to specifying welfare in this manner is that households may have high WTP for reasons that have nothing to do with the disaster. A household may be liquidity constrained due to a sequence of bad harvests, or unrelated macroeconomic factors, for example. On the other hand, this can be seen as a positive feature of this SWF, since what is determined to be a 'disaster' may be quite arbitrary (Strömberg, 2007). It's hard to imagine that these arbitrary considerations matter much to the potential recipients of the aid.

To be precise, however, this measure of demand is appropriate for analyzing a policy that aims to improve consumption smoothing, and would be appropriate for a planner that wants to use disaster aid as a form of social-insurance. Thus one way of interpreting these results is as a measure of what fraction of the shocks faced by households in the survey are related to earthquake induced property damages.

For our main results, we compare various allocations of aid according to both the utilitarian ($\alpha_i = 1$) and WTP for consumption smoothing ($\alpha_i = (\frac{\Delta V}{\Delta P_{it}})^{-1}$) criteria. However, we also look at 'reduced form' social welfare functions, where the planner only cares about the aggregate effects on rebuilding or on household consumption.

Lastly, it is important to note that, since the data is collected starting from one year after the earthquake, these results are best interpreted as relevant for long-term reconstruction aid, rather than emergency aid. In fact, long-term reconstruction was the primary goal of the major aid program that we analyze. Smaller amounts of aid an in-kind goods were distributed in the immediate aftermath of the earthquake, but most of the total aid budget was disbursed one to three years after the earthquake, which is not uncommon for major disasters.

3.1. *Structural Model of Household Reconstruction*

In order to estimate welfare under various counterfactual targeting policies, we need to put more structure on the household value function. We capture key sources of heterogeneity in a standard dynamic model of incomplete insurance (Deaton, 1991, Kaboski and

Townsend, 2011) that incorporates the option to invest in a durable housing stock (Yang, 2009).

Households choose consumption c, and housing investment ι to maximize an infinite discounted stream of utility deriving from consumption and a housing stock, h:

$$U_i = E[\sum_{t=0}^{\infty} \beta^t u(c_{it}, h_{it})]. \tag{5}$$

Flow utility takes a standard isoelastic functional form: $u(c_{it}, h_{it}) = \left(\frac{c_{it}^{\alpha} h_{it}^{1-\alpha}}{1-\gamma}\right)^{1-\gamma}$, that allows for estimation of the importance of housing relative to consumption, as well as risk aversion between periods. h_{it} measures the economic value of the housing stock, which evolves according to:

$$h_{it} = \delta(h_{it-1}) + \iota_{it} \tag{6}$$

where δ is the depreciation factor.[4] In each period, households receive income Y_{it}, drawn from $log(Y_{it}) \sim N(\mu_{it}, \sigma^2)$. This allows households to differ in their expected earnings, but they are assumed to have a common variance of log income. Given the income process, household expected income is $\exp(\mu_{it} + \sigma^2/2) := P_{it}$.

In order to smooth consumption, households can borrow and save at interest rate R. Liquidity at the beginning of each period is denoted as x_{it}, which evolves according to:

$$x_{it+1} = R(x_{it} - c_{it} - \iota_{it}) + Y_{it+1}. \tag{7}$$

Finally, housing markets are illiquid, and households are subject to a borrowing constraint, B, so households choose c and ι to maximize (5) subject to (6), (7), and:

$$x_{it} - c_{it} - \iota_{it} \geq B \tag{8}$$

[4]We assume housing investment is continuous, in contrast to some previous work that models lumpy investments in housing. This simplification is justifiable in the Nepal context, where many households returned to partially destroyed homes, and reconstruction was an ongoing process. Since households rebuilt their own homes, there were no transaction costs associated with buying and selling homes, a key component of the lumpiness of housing investment in richer countries. Furthermore, the positivity constraint on housing investment acts like lumpiness, in that it creates a mass of households with $\iota = 0$, matching what we see in the data.

$$\iota_{it} \geq 0. \tag{9}$$

The latter constraint ensures that households cannot liquidate their housing stock to fund consumption, which is a realistic feature of rural housing markets in many low-income countries. Because B may be negative, if x_{it} is sufficiently close to B, and $R > 1$, a household could exceed the borrowing constraint, with $x_{it+1} < B$ even if c_{it} and ι_{it} are zero. To avoid this, we follow Kaboski and Townsend (2011) in allowing households to default. In the case of default, households receive a minimum consumption and housing bundle:

$$c_{it} = \underline{c}; \iota_{it} = 0; h_{it} = \max[h_{it}, \underline{h}]; x_{it+1} = RB + Y_{it+1} \tag{10}$$

These minimum consumption and housing bundles, as well as the borrowing limit B are assumed to be some fraction of permanent income: $\underline{c} = \bar{c}P_i$, $\underline{h} = \bar{h}P_i$, and $B = \lambda P_i$, where $\bar{c}, \bar{h}$, and λ are parameters to be estimated.

The effects of the earthquake are can show up through the values of any of the state variables – a destroyed housing stock would result in lower h_{it}, a liquidity shortfall (i.e. as a result of a temporary income shock) would result in lower x_{it}, and reduced expected future earnings would manifest as a lower P_{it}.

Aid (a_{it}) is modelled as additive to liquidity such that $x_{it+1} = R(x_{it} + a_{it} - c_{it} - \iota_{it}) + Y_{it+1}$. While the aid was supposed to be used for building earthquake resilient housing, this specification allows for a certain degree of fungibility, and for reasonable parameter values, households with low housing stock will use the extra liquidity for investment.

Finally, all state and control variables are normalized by expected income, P_{it}, which reduces the dimensionality of the state space. If $V(\cdot)$ is the value function associated with the maximization of (5), define $\nu(\cdot) = P_{it}^{\gamma-1}V(\cdot)$. This allows us to express x, h, c, and ι as fractions of expected income, which is done below without changing notation. Redefine y_{it} as the log-normal random variable Y_{it} divided by its expected value: P_{it}. Note that $log(y_{it}) = log(\frac{Y_{it}}{M_{it}}) \sim N(-\frac{\sigma^2}{2}, \sigma^2)$. For more details see Appendix A.

Combining (5) - (10), the households problem can be written recursively, with the Bellman equation:

$$P_{it}^{\gamma-1}V(x_{it}, h_{it}|P_{it}) = \nu(x_{it}, h_{it}) = \max_{d_i}\left\{d_i\nu_{d=1}(h_{it}) + (1-d_i)\nu_{d=0}(x_{it}, h_{it})\right\} \tag{11}$$

with

$$\nu_{d=1}(h_{it}) = u(\bar{c}, \max[h_{it}, \bar{h}], 0) + \beta E\Big[\nu\big(R\lambda + y_{it+1}, \delta \max[h_{it}, \bar{h}]\big)\Big], \text{ and}$$
$$\nu_{d=0}(x_{it}, h_{it}) = \max_{c_{it}, \iota_{it}} u(c_{it}, h_{it}) + \beta E\Big[\nu\Big(R(x_{it} - c_{it} - \iota_{it}) + y_{it+1}, \delta h_{it} + i_{t+1}\Big)\Big]$$

subject to the normalized versions of constraints (8) and (9).

$\nu_{d=0}(x_{it}, h_{it})$ is the household value function without defaulting, and $\nu_{d=1}(h_{it})$ is the value of defaulting and consuming the minimum consumption and housing bundle.

With this normalization, we can solve analytically for τ, the percentage of expected future income a household would be willing to give up in exchange for aid:

$$\tau_i = 1 - \left[\frac{\nu(x_{it}, h_{it})}{\nu(x_{it} + a_{it}, h_{it})}\right]^{\frac{1}{1-\gamma}}. \tag{12}$$

Since τ_i only depends on liquid wealth and housing wealth, it is simple to use equation 3 to study how household WTP for aid changes with different assumptions about how the earthquake or aid changes permanent income.

The model introduces a lot of structure to household decision making. Several assumptions are worth discussing in more detail. First of all, the model is partial equilibrium, with exogenous income processes and interest rates. While a general equilibrium model would certainly be of interest, given the cost in terms of complexity, a partial equilibrium approach can be justified given that we hold the total amount of aid constant across all counterfactuals. Even if inflows of aid have macro-economic consequences, it is less likely that different allocations of the same amount of aid would have dramatically different implications for credit or input markets.

Secondly, this framework does not allow for externalities resulting from household decisions. In their structural analysis of disaster aid in the aftermath of Hurricane Katrina, Fu and Gregory (2019) find the existence of rebuilding externalities. Agglomeration economies are less important in rural Nepal than in New Orleans, possibly reducing the importance of these externalities. On the other hand, to make their model tractable, Fu and Gregory (2019)'s model features deterministic income, whereas in rural Nepal income is stochastic and highly variable, justifying a shift in emphasis. Furthermore, since the rental market is virtually non-existent, there are no pecuniary externalities through housing prices, which could be important if a disaster created a housing shortage. Rather than search for market based rental housing, most households lived in temporary shelters close to their original dwellings or moved back into their partially reconstructed homes (The Asia Foundation, 2016*a*). A more plausible type of externality in this setting would be increasing liquidity throughout the aid recipient's network, which would make targeting based on observable damages less important.

Finally, the permanent component of income, μ_{it}, is taken as exogenous to choice and state variables. While endogenizing income would be possible with additional parameters (see e.g. Kaboski and Townsend 2011), this more parsimonious and tractable specification can be justified for two reasons. First, it is consistent with the findings of the post-disaster needs assessment and the survey data discussed above, that emphasized the effects of the earthquake on housing rather than on income or productive assets. We test whether earthquake losses are associated with lower income and can reject even fairly small negative effects (Appendix Table C.I). Secondly, since the survey data only covers the period following the earthquake, expected income should be thought of as post-earthquake expected income – which is what would be recorded in a post-disaster needs assessment, and what defines our measure of willingness-to-pay. Section 5.1 explores some ways of relaxing this assumption, and allowing permanent income to respond to the receipt of aid.

Despite these limitations, the key features of the model are informed by the data and context. Furthermore, when fit to the data, this structure permits an analysis of the relative importance of housing investments, consumption, and savings. The way households make tradeoffs between these choices will allow us to coherently define a notion of a household's demand for aid and analyze the welfare of counterfactual targeting strategies.

3.2. *Mapping the Model to Data*

In order to estimate individual households' marginal utility and WTP for aid, we map our model of consumption, savings, and reconstruction to the household survey data. The model has three state variables: x_{it}, h_{it}, P_{it}, two continuous choice variables: c_{it}, ι_{it}, and a binary decision to default: d_{it}. The three state variables summarize the sources of household heterogeneity. We use the choice variables to define moment conditions to estimate model parameters in the following section.

The WBHRVS data contains detailed consumption information, we construct c_{it} using all categories of non-durables, which is mostly food consumption. The survey also includes information on household repair, maintenance, home improvements, and additions, which are taken to be ι_{it}. The survey asks households what they would have to pay to purchase a home like this today. Since this value should include the value of any additions or repairs undertaken during the survey year, we used the lagged value as an estimate of h_{it}. This variable captures earthquake damages well – households that report experiencing earthquake damages have an average housing value 46% lower than households that don't report damages in the first survey wave (before aid was disbursed).

The y_{it}s are the realizations of household income in each period, which includes wages, agricultural sales (including home food production), business revenues and capital income. P_{it} is estimated as the predicted values of income from a regression of income on a vector of household characteristics, as well as survey-year fixed effects to capture the macroeconomic cycle (details in Appendix A).

Beginning of period liquidity, x_{it}, includes lagged cash savings minus debts owed, capital gains, income, aid received, as well as new loans taken and informal transfers, including remittances. Since the model does not allow for investments in income, we restrict attention to short-term consumption loans (term less than three years and taken within the past three years), and calculate estimated annuities based on each loans' term and interest rate. Similar to Kaboski and Townsend (2011), we define default, d_{it}, as having an outstanding loan balance more than six months after the term of the loan has expired.

Finally, to account for unmodelled variation from the business cycle, and household age structure, size, and education levels, we purge these sources of variation from the data, again following the approach in Kaboski and Townsend (2011). Full details are in Appendix A.

Finally, we follow Kaboski and Townsend (2011) by introducing multiplicative measurement error in household expected income. Measurement error is an important concern, and it could affect parameter estimates, since errors that induce fluctuations in income that do not correspond to changes in consumption will make households appear to be more insured than they are in reality. Furthermore, since estimates of household expected incomes are imperfect, the variance of household income shocks in the data may be greater than in reality. For each household, we draw a vector of 100 log normally distributed measurement error shocks with log variance of σ_m. The P_{it}s are then multiplied by the vector of simulated measurement error shocks. Since all other state and choice are normalized by expected income, this introduces measurement error in those variables as well. We then match moments using this simulated data.

4. MODEL ESTIMATION AND VALIDATION

After adding measurement error, the model has ten parameters: $\theta = [\beta, \gamma, \alpha,\ R, \delta, \bar{c}, \bar{h}, \lambda, \sigma, \sigma_m]$. We will estimate these parameters by defining a vector of moment conditions derived from the model and applying the method of simulated moments with the optimal weighting matrix (Hansen, 1982).

There are 17 moment conditions in total. The first 9 moments aim to match model predictions of consumption, reconstruction and default with household behavior in the data, as well as interactions of the deviations in these predictions with household state variables. Another three moments pin down R using data on returns to savings and interest rates payments on loans taken and received. Two moments help to identify σ and σ_m by matching the first and second moments of household income processes to their expectations. Another moment identifies δ using a hedonic style regression on the age of the housing stock. These 15 moments are elaborated in greater detail in Appendix A.

While these moments are consistent with the internal structure of the model, there could be unobserved or unmodelled sources of household heterogeneity that influence parameter estimates. Thus we add two additional moments derived using an exogenous source of variation in access to liquidity. In particular, during the period covered by our survey, aid was targeted at households living in the fourteen most affected districts (see Figure 1). Households close to the borders of these fourteen districts, but on opposite sides of the boundary are expected to have similar levels of earthquake damages, as well as similar geographic, demographic, and economic characteristics. However they differ in their probabilities of receiving aid. This exogenous liquidity shock can help us to pin down policy function responses to a change in liquidity. Thus our final two moments take the form:

$$e_{i,16} = \frac{d}{da_{it}} \log c^*(x_{it}, h_{it}, P_{it}) - E(\frac{d \log c_{it}}{da_{it}}) \quad | \quad a_i > 0 \tag{13}$$

$$e_{i,17} = \frac{d}{da_{it}} \log \iota^*(x_{it}, h_{it}, P_{it}) - E(\frac{d \log \iota_{it}}{da_{it}}) \quad | \quad a_i > 0.$$

The first term on the right side of each equation represents the change in the log of the optimal policy function response to a change in liquidity. It is calculated by taking the difference between the log of model predicted consumption and housing investment with observed liquidity, minus any aid received, and the log of the predictions with observed liquidity, plus 300,000 NPR, corresponding to the size of the aid package. For $e_{i,17}$, we take the log of $\iota + 1$ to deal with zeros. The following sections describe how we estimate $E(\frac{d \log c_{it}}{da_{it}})$ and $E(\frac{d \log \iota_{it}}{da_{it}})$, the causal effects of aid on consumption and housing investment. Since we can only estimate these quantities in our data for households that received aid, which was conditional on housing damages,[5] we only estimate these moments for households that received aid ($a_i > 0$).

4.1. *Regression Discontinuity Estimates of the Effects of Aid*

Receipt of aid is endogenous to observed and unobserved earthquake damages, which are likely to be correlated with outcomes of interest, including consumption, income, savings, and housing investment. In addition, the earthquake occurred in a distinctive region of the country – disproportionately affecting the mountainous districts surrounding Kathmandu. To estimate the causal effects of aid, we rely on an administrative feature of the reconstruction aid program – aid was prioritized for the fourteen most affected districts. In 2018, 60% of eligible households in the most affected districts (red and orange in Figure 1) had received at least 2 tranches of aid, whereas, only 15% of eligible households in the moderately affected districts (yellow, green, and blue in Figure 1) had received the same (Housing Recovery and Reconstruction Platform, 2018).

These features of the response suggest the use of a spatial regression discontinuity (RD) approach to compare outcomes between households close to the borders of the designated districts. Thus we estimate the following regression:

$$Z_{it} = \beta_1 \widehat{\text{Aid}}_{it} + \beta_2 D_i + \beta_3 D_i \mathbf{1}_{\{D_i > 0\}} + e_{it}. \tag{14}$$

[5] In fact, section 5 highlights how the estimated causal effects of aid change according to different targeting strategies.

Z_{it} is an outcome variable for household i at time t. Aid_{it} is a dummy variable for whether a household has received at least their first tranche of aid by time period t, and it is instrumented with a dummy variable for whether a household is on the 'right' side of the border $(\mathbf{1}_{\{D_i>0\}})$, making this a fuzzy RD specification. β_1 thus gives us $E(\frac{d \log Z_{it}}{da_{it}})$, which, when Z is consumption and housing investment in turn, gives us the estimates we need to construct the final two moment conditions.

The running variable D_i is distance from each household to the western border of the 14 most affected districts.[6] The specification allows the slope of the running variable to differ on either side of the border. Cattaneo, Idrobo and Titiunik (2020) also suggest using distance to a specific point on the border for two dimensional regression discontinuity applications rather than distance to the entire border, so we also show a specification that uses distance to the point on the border that is closest to a village.

In some specifications we include a vector of control variables, which include self-reported earthquake damages, age and education of the household head, a high-caste dummy, and the travel time to the nearest health clinic.

Since the RD analysis restricts the regression to a subset of 'border' households, one of the crucial parameters for the RD analysis is determining the bandwidth within which a household is included in the regression. A wider bandwidth typically allows for more precision, at the cost of biased estimates if there is curvature in the slope of the running variable near the border point. We use the methods from Calonico et al. (2017) and Calonico, Cattaneo and Farrell (2020) to calculate the optimal bandwidths for point-estimation and inference, which vary for each dependent variable, typically falling between 25 and 60 km in the main specifications. We test robustness to alternate bandwidths in Appendix B. The blue dots in Figure 1 indicate villages that fall within the bandwidth for inference for the first stage regression – 60 km. All regressions use kernel times survey weights. The kernel weights give more weight to households closer to the border, allowing us to control for dis-

[6]We also show robustness to using the entire border in Appendix B. The western border is used as it is close to the epicenter of the earthquake and features comparable geography and earthquake damages across the border. The southern border of the 14 districts is the geographic boundary with the Terai (plains region of Nepal), and earthquake damages were much lower in these districts, as well as along the eastern border.

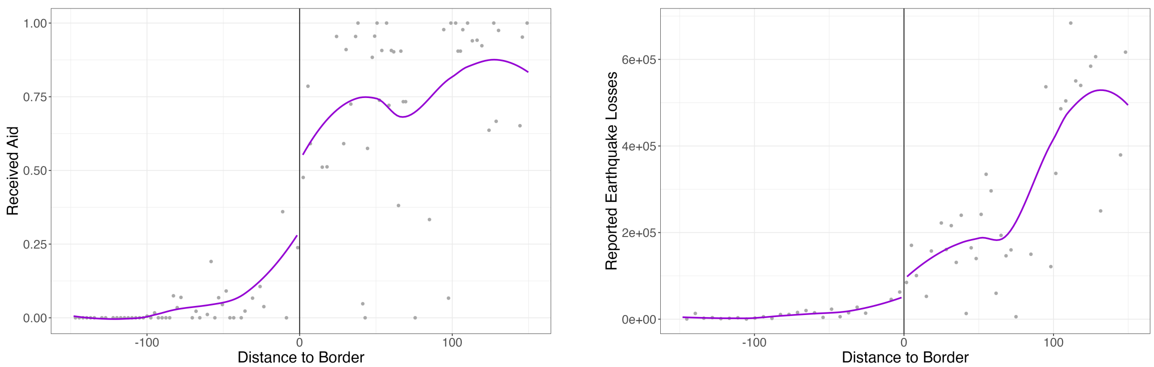

FIGURE 2.—Binned averages of fraction of households receiving aid and self-reported earthquake damages as a function of distance to the border

with Loess smoothing.

tance to the border non-parametrically[7]. We use heteroskedasticity-robust standard errors following the recommendations of Kolesár and Rothe (2018) in settings where the running variable is discrete.

Figure 2 shows the identification strategy graphically. The left panel shows the binned averages of the probability of receiving aid as a function of distance to the border point. There is a clear jump in the probability of receiving aid at the border. The right panel shows self-reported earthquake damages plotted in the same way – there is no comparable discontinuity. The results of the first stage regression show that households just inside the border of the most affected districts were 23% more likely to receive aid, and received nearly 40,000 NPR more aid on average in the primary specification (Appendix Table B.V). Alternative specifications give mostly similar results, including different choices of bandwidth, kernel, distance to alternate border points, inclusion of less affected districts, inclusion of control variables, and a 'donut hole' specification that excludes villages within 5 km of the border.

4.1.1. *Identification Assumptions*

For β_1 to accurately identify the causal effects of aid, it must be the case that the receipt of aid is the only thing that changes discontinuously at the border. Other political, institutional,

[7]We use triangular weights in the baseline specification and test sensitivity to alternative kernels in Appendix B.

and geographic factors must be a continuous function of geography, and in particular there cannot be sorting across the border – a potent concern in spatial RD settings as discussed by Keele and Titiunik (2015).

These assumptions hold in this setting for two reasons. First, pre-quake political institutions in Nepal were weak as discussed in Section 2. The district borders were mostly set in the 1960s during the Panchayat Regime – a system of governance in which district representatives were elected to serve on a partyless National Assembly that was powerless to do anything other than rubber-stamp the King's agenda. For these reasons, there shouldn't be large differences in policy across district boundaries. Furthermore, district borders do not demarcate boundaries between ethnic groups, giving us no reason to believe that informal institutions change discretely at the border either (Gurung, Gurung and Chidi, 2006).

Regarding sorting, land and housing markets in rural Nepal are not very liquid. While rural to urban and international migration are important livelihood strategies, rural-to-rural migration is rare. If entire households migrated away from regions that did not receive aid, this could also be problematic. It is much more common for one or two individuals within a household to migrate and send back remittances, however.[8]

As suggested by Imbens and Lemieux (2008), we can gain confidence in the underlying RD assumptions by conducting placebo tests on household demographic, political, and geographic variables. To do so we run versions of equation (14), replacing Z with placebo variables that should not change with the receipt of aid. For this exercise, we compare households baseline characteristics using data from the first wave of the survey, immediately after the earthquake, but before aid had been disbursed.

Most household demographic variables appear smooth at the border, although some are noisy (Appendix Figures B.4). Table B.VI formally tests for discontinuities, and finds no significant differences in self-reported damages, caste, age, the number of household members, the probability that a household member has completed 5 or 10 years of schooling, or the fraction of households that have always lived in the same house or same district on either side of the border, supporting the idea that household demographics are compara-

[8]A McCrary test for discontinuities in the density of households on either side of the border is not informative in this setting because the sample frame for the survey is based on the 2010 census, but sampling occurred after the earthquake in 2015 (McCrary, 2008) We plot the density of households as a function of distance to the border anyway and do not observe any obvious discontinuities (see Appendix B).

ble. We also find no differences in the receipt of NGO aid or non-earthquake government transfers, supporting the hypothesis of no policy changes at the border.

We also test for differences in prices of common food items, as well as for travel times to the nearest bank, school, market, and healthcare clinic as a proxy for market integration and public good provision, and we find no differences. Differences in elevation across the border are not significant, but there is a difference in slope that is significant at 5%. This significance does not survive using Calonico, Cattaneo and Farrell (2020) robust confidence intervals, and correcting p-values for multiple hypothesis testing, however.[9]

4.1.2. *The Causal Effects of Disaster Aid*

Turning attention to outcomes of interest, the main specification in the first row of Table III shows large effects of aid on log consumption and home investment, and large negative effects on remittances and migration[10]. Effects on savings, loans, investments, and income are not distinguishable from zero. Figure 3 shows the discontinuities for these variables in the data, which are clearly visible for housing investment and remittances. Similar plots for additional variables, including the placebos, appear in Appendix B.

We also show robustness to alternative choices of kernel, bandwidth, control variables, and dependent variable functional form in Appendix B. Main results on consumption, investment and remittances are highly robust to these variations, although the point estimate on remittances is somewhat noisy. In some specifications we also find a positive and significant effect effect on new loans taken, and/or income. We also test robustness of the results to using different definitions of the running variable, such as including the eastern and southern border segments, or using distance to a specific point on the border. This leads to somewhat noisier estimates for all variables, especially for consumption, but we still see big positive point estimates on home investment, and big negative point estimates on remittances in all specifications.

[9]Using distance to the single point, rather than distance to the full border shows significant differences in self-reported damages, NGO transfers, and some of the travel time and geographic variables, however none of these differences remain significantly different from zero using Calonico, Cattaneo and Farrell (2020) robust confidence intervals and correction for multiple hypothesis testing.

[10]After using Calonico, Cattaneo and Farrell (2020) confidence intervals and correction for multiple hypothesis testing, the effects on consumption and home investment remain significant at 5%, though the p-values for the effects on remittances and migration are above 10%.

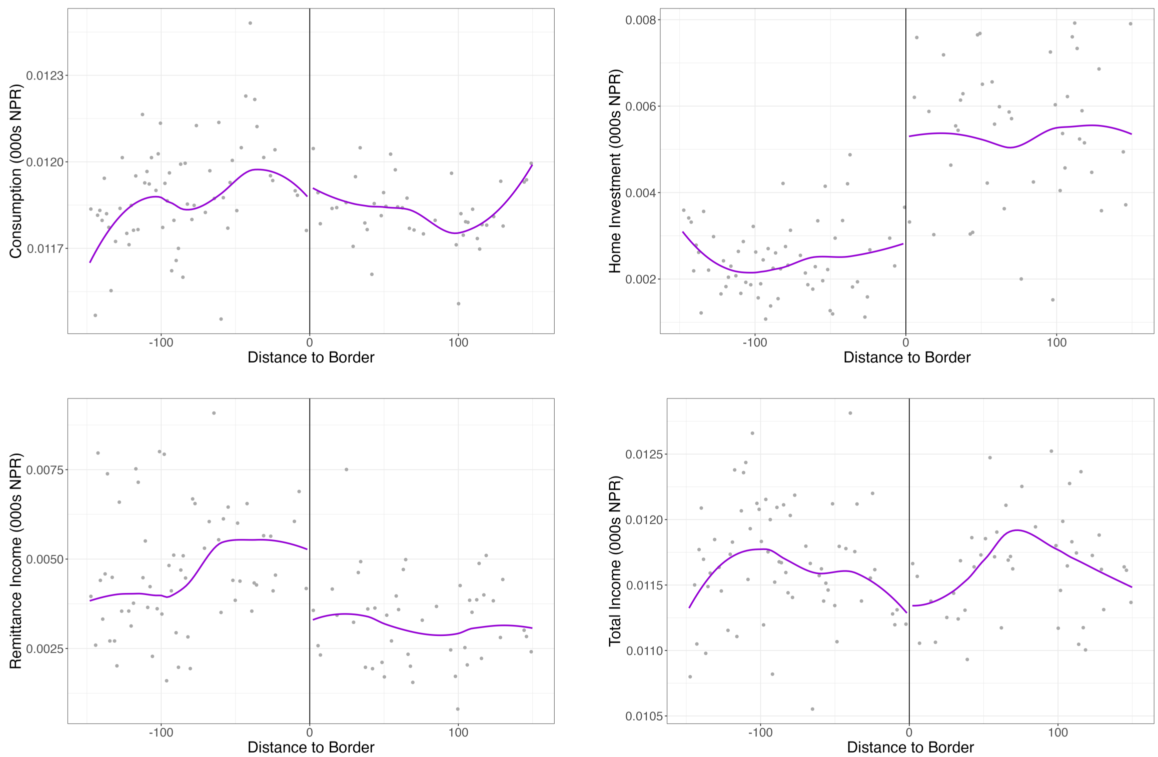

FIGURE 3.—RD Plots: Binned averages of outcome variables as a function of distance to the border with Loess smoothing. Positive values indicate villages inside the districts that were prioritized for aid.

These estimates are qualitatively consistent with the structural model's predictions. Households increase both consumption and investment, showing that aid is somewhat fungible, even though it was supposed to be used for housing reconstruction. Aid also substituted for other sources of liquidity, in particular remittances, which are an important source of informal insurance in Nepal, as discussed in Section 2. Given the estimates on new loans taken, we have some weak evidence that aid may have induced additional borrowing, which would be consistent with additional liquidity relaxing a borrowing constraint. These results give some support to the model being a reasonable approximation of household decision making in this context, and thus, once properly calibrated, can be informative about household values for aid. In calibrating the model, we take our estimates from the first two columns of Table III to construct moment conditions e_{16} and e_{17}, setting $E(\frac{d\log c_{it}}{da_{it}}|a_i > 0) = 0.66$, and $E(\frac{d\log \iota_{it}}{da_{it}}|a_i > 0) = 9.79$.

	consumption	home investment	remittance income	cash savings	new loans taken	investments	total income	migration
Regression Discontinuity Estimates: Distance to Western Border								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Aid}$	0.66^{**}	9.79^{***}	-6.47^{**}	0.90	5.69	1.25	0.93	-0.76^{**}
	(0.32)	(3.77)	(3.20)	(2.54)	(3.57)	(2.56)	(0.61)	(0.37)
N	1042	1435	695	1071	916	1310	476	1093
Bandwidth	33.89	42.28	25.33	34.14	31.34	38.83	22.05	34.92
Wards	66	66	35	46	40	77	35	45
Regression Discontinuity Estimates: Distance to Single Point								
	consumption	home investment	remittance income	cash savings	new loans taken	investments	total income	migration
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Aid}$	0.34^{*}	4.15^{*}	-5.13^{*}	0.85	4.13^{*}	0.37	1.26^{*}	-0.38
	(0.20)	(2.13)	(2.97)	(1.88)	(2.21)	(1.82)	(0.66)	(0.26)
N	432	1873	1047	1550	1793	1658	1220	1224
Bandwidth	29.14	59.68	41.67	50.47	56.39	53.51	43.02	42.74
Wards	34	85	55	76	79	85	57	57
Model Predictions: Response to 300k Aid								
	food consumption	home investment	borrowing					
	(1)	(2)	(3)					
Aid	0.23	2.19	-7.12					
	(0.24)	(3.20)	(9.90)					

TABLE III

POLICY FUNCTION ESTIMATES

Top panel shows regression discontinuity estimates using local linear regressions with triangular kernel times survey weights, heteroskedasticity-robust standard errors, and optimal bandwidths. Slope of running variable allowed to differ on either side of cutoff. Distance > 0 used as instrument for aid. All dependent variables in logs, with 1 added to home investment, remittances, cash savings, loans, investments, and migration to account for zeros. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels respectively. Bottom panel shows calibrated model predicted effects on choice variables for households that actually received aid. Population estimated standard deviations in parentheses.

4.2. *Model Validation*

The parameter values that minimize the MSM objective function are shown in Table IV. In comparison to Kaboski and Townsend (2011), we find a notably high coefficient of risk aversion, and a low discount factor, indicating rather extreme risk aversion and present bias. This difference arises for a few different reasons. First, Kaboski and Townsend (2011) did not observe cash holdings, so we have a more comprehensive measure of liquid wealth. Holding more wealth makes households look more risk averse. Secondly, the structure of the economy in Nepal is different, with much higher reliance on remittances. Thus liquidity-to-permanent income ratios are much higher in this context, also explaining why we find a borrowing constraint (λ) that is relatively high as a fraction of permanent income. Finally, previous work has suggested that exposure to natural disasters may increase risk-aversion (Cameron and Shah, 2015). It is plausible that this mechanism is also at play in this setting. We use these values for our primary counterfactuals, but we also show robustness of our results to using risk-aversion and discount-factor parameters from Kaboski and Townsend (2011) in Section 5.1.

In terms of the other parameters, interest rates are very low, which is not uncommon in a low-income context, as few households earn interest on their cash holdings. Depreciation rates and the Cobb-Douglass share on consumption are both within the range of normal values in the literature, and the minimum consumption bundle ($\bar{c}$) is comparable to what Kaboski and Townsend (2011) estimate, when accounting for the Cobb-Douglass share of consumption. The minimum housing bundle associated with default is a new parameter, so we lack relevant sources of comparison. For a household at the average income level, this indicates a value of housing stock in default at about \$2,600. Median and mean home values in the survey are 2 and 4.5 times larger respectively. This parameter thus could be consistent with reports suggesting many earthquake-affected households moved in with friends and family, or moved into partially reconstructed houses. Since results about targeting based on housing damage are likely to be sensitive to household's outside options for housing, we test sensitivity to this parameter in Section 5.1.

Using the estimated model, we can calculate each household's marginal utility and WTP for aid, which will allow us to compare aggregate welfare from different targeting strategies. But first, to ensure that the model is capturing something real in the way households value aid, we perform several validation exercises.

In terms of targeted moments, the third row of Table III compares the regression discontinuity estimates to the model predictions by calculating counterfactual consumption, investment, and borrowing responses to aid using the optimal policy and investment functions from Section 4. We restrict attention to the households that actually received aid, since the model predictions differ for different subsets of households. We subtract any aid received from each household's liquidity and calculate predicted consumption, investment, and borrowing. Then we add back 300,000 NPR, and calculate consumption, investment, and borrowing again.

Variable	Definition	Source
c_{it}	Consumption	Value of last week's food consumption in survey multiplied by 52, plus annual spending on utilities, transportation, clothing, and entertainment.
ι_{it}	Housing Investment	Spending on home repairs, improvements, maintenance, furniture, and large appliances over the last 12 months.
d_{it}	Default	1 if a household has unpaid debts more than 3 months past the term of the loan, otherwise 0.
Y_{it}	Realized Income	Income from wages, agricultural sales, food home production, land, housing, and equipment rentals, and pensions and other government programs.
P_{it}	Expected Income	Estimated from household characteristics, see Appendix A.
x_{it}	Liquid Wealth	Lagged cash savings minus debts owed, capital gains, income, aid received, as well as new loans taken and informal transfers and remittances
h_{it}	Housing Wealth	Lagged estimate of self-reported value from survey. Age of housing stock also used to estimate depreciation.

Parameter	Estimate (SE)	Interpretation
γ	4.46 (0.04)	Coefficient of Risk Aversion
β	0.88 (0.02)	Discount Factor
α	0.75 (0.01)	Cobb-Douglass Share on Consumption
δ	0.95 (0.01)	Depreciation Factor for Housing
R	1.001 (0.001)	Interest Rate (+1)
$\bar{c}$	0.27 (0.01)	Minimum Consumption as Fraction of Expected Income
$\bar{h}$	0.95 (0.09)	Minimum Housing as Fraction of Expected Income
λ	0.53 (0.02)	Borrowing Constraint as Fraction of Expected Income
σ	1.03 (0.02)	Standard Deviation of Log Income
σ_m	0.02 (0.09)	Standard Deviation of Log Measurement Error

TABLE IV

MODEL VARIABLES AND ESTIMATED PARAMETERS

The model predicts smaller effects on consumption and housing investment than we observe in the RD, although they are closer to the effects estimated using the single point cutoff design, suggesting that there could be substantial treatment effect heterogeneity – as the model predicts, as shown by the large standard deviations in the effects of aid on consumption and investment in Table III. Although it was not used as a targeted moment, the model's predicted effect on borrowing is well aligned with the estimated effects on remittances from the RD.

Since one of our primary objectives is to study how different targeting policies correlate with demand for liquidity to smooth consumption, we validate our estimates of WTP, by looking at whether the values correlate with household characteristics and behaviors that relate to consumption smoothing. Table V shows regressions of estimated WTP on household characteristics in panel A and strategies for coping with shocks in panel B.

In panel A, we see that Newari households have lower WTP for aid relative to Brahmin/Chhetri households, and Dalit and other castes have higher WTP. Land-rich households also have lower WTP for aid – they are willing to give up 2.6% less of their expected future income in exchange for liquidity now. This is consistent with the findings in Table I, that these households are better able to smooth consumption. On the other hand, we find that female-headed households have higher willingness-to-pay for aid, contrary to the findings of in Table I that showed that these households are better on average at consumption smoothing. One possible explanation is that, since these results are based on a cross-section rather than the full panel, household composition changes over time, and some of these households may recently sent a migrant, but not yet received remittances. The final column shows that earthquake-affected households do indeed have higher WTP for aid, but the coefficient is smaller in magnitude than for some of the other household characteristics.

In panel B, we perform further validation checks by seeing whether our measure of WTP is correlated with self-reported household strategies for coping with shocks. Column 1 uses as the independent variable the maximum interest rate on an outstanding household loan. Households that are paying higher interest rates have higher WTP, supporting the interpretation of WTP as demand for liquidity. Columns 2-5 show that WTP is higher among households that reported spending down their savings in the past year, households that cut down on food consumption, households that had a migrant member, and households that reported a child under the age of 18 engaging in either work activities, although some of the relationships are not statistically significant. In particular, households that report having a child working are willing to give up 1.7% more of their future income in order to access aid now. Although these regressions are descriptive and simple, the findings support the interpretation of WTP as the need for liquidity to smooth consumption.

5. COUNTERFACTUAL REALLOCATIONS

We analyze a variety of targeting policies, using our measures of WTP to assess the aggregate surplus created by different aid allocations. We normalize welfare relative to a baseline “random allocation" scenario, which sets benefits equal to the population average WTP. We also analyze the surplus created by the actual allocation of aid.

As discussed above, household WTP is increasing in expected future income. Thus, an allocation could result in low welfare gains if it prioritizes of low-income households. Therefore, we also compare targeting strategies using a utilitarian social welfare function. This criterion prioritizes poor households with a high marginal utility for liquidity. Furthermore, we show the aggregate effects of each allocation on consumption and housing reconstruction. Full results for all welfare measures and targeting schemes are reported in Table D.I.

All counterfactuals are analyzed based on WTP in the second survey wave, which is when most aid-eligible households received the first tranche of reconstruction aid. This will somewhat overstate the value of the actual allocation of aid, since some households didn’t get the aid until later, and those that did received aid in several tranches over multiple years. This approach analyzes the value of receiving all the aid at once. We subtract any aid received from household liquidity to get estimates of pre-aid WTP. Since we use lagged measures of the housing stock, that state variable reflects the state of the housing stock in the first survey wave, right after the earthquake, and is thus uncontaminated by the effects of aid. We also restrict the analysis to the earthquake affected districts (including moderately and slightly affected districts) to set a reasonable restriction on the eligible population. 58% of households in these districts reported experiencing earthquake damages, and an estimated 38% of households received aid.

In all counterfactuals, except for the universal allocation, we hold the fraction of households receiving aid constant. In the universal allocation, we hold the budget constant, by

A. Household Characteristics

	WTP as Fraction of Income in Percentage Points			
	(1)	(2)	(3)	(4)
(Intercept)	12.93***	12.40***	14.81***	13.07***
	(0.31)	(0.21)	(0.26)	(0.28)
Dalit	1.64***			
	(0.62)			
Newar	−1.50*			
	(0.89)			
Other	0.97**			
	(0.41)			
Female Head		4.67***		
		(0.42)		
Land > Median			−2.64***	
			(0.37)	
Quake Affected				0.77**
				(0.37)
Num.Obs.	2086	2086	2086	2086
R2	0.008	0.056	0.025	0.002

B. Household Coping Strategies

	WTP as Fraction of Income in Percentage Points				
	(1)	(2)	(3)	(4)	(5)
(Intercept)	12.73***	13.33***	13.49***	13.38***	13.32***
	(0.26)	(0.22)	(0.19)	(0.20)	(0.19)
Max Interest Rate	0.06***				
	(0.01)				
Spent Savings		0.62			
		(0.40)			
Cut Food Consumption			1.06		
			(1.20)		
Migration				0.53*	
				(0.27)	
Children Worked					1.73**
					(0.57)
Num.Obs.	2086	2086	2086	2086	2086
R2	0.009	0.001	0.000	0.002	0.004

TABLE V

REGRESSIONS OF WTP FOR AID AS A PERCENT OF FUTURE INCOME (IN PERCENTAGE POINTS) ON HOUSEHOLD CHARACTERISTICS (PANEL A) AND SELF-REPORTED COPING STRATEGIES (PANEL B). Household characteristics are defined as in Table I. Coping strategies are the maximum interest rate paid on an outstanding household loan, and dummies for whether a household reports spending savings, cutting food consumption, having a migrant member, and having a child under the age of 18 engaged in agricultural or non-agricultural labor. Sample is second wave of WBHRVS, households in earthquake affected districts, the same as what is used for counterfactuals. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels respectively.

Welfare Measure	Actual (1)	Damages (2)	Shake Intensity (3)	Consumption (4)	Liquidity (5)	Universal (6)	Optimal (7)
	Targeting Scenario						
WTP	1.05	1.06	1.08	0.99	1.00	1.04	1.52
	(1.02, 1.08)	(1.03, 1.09)	(1.04, 1.10)	(0.95, 1.02)	(0.96, 1.03)	(1.02, 1.06)	(1.46, 1.53)
Utilitarian	0.52	0.59	0.35	1.36	2.16	0.91	2.62
	(0.24, 0.73)	(0.27, 0.80)	(0.16, 0.49)	(0.85, 1.76)	(1.97, 2.38)	(0.65, 1.15)	(2.54, 2.81)
Consumption Increase	0.92	0.90	0.89	1.08	1.57	1.02	2.00
	(0.87, 0.98)	(0.86, 0.96)	(0.82, 0.93)	(1.01, 1.13)	(1.52, 1.62)	(0.97, 1.08)	(1.98, 2.11)
Housing Increase	1.11	1.07	1.03	1.09	1.36	1.09	2.43
	(1.02, 1.19)	(0.98, 1.15)	(0.95, 1.12)	(1.00, 1.16)	(1.65, 1.82)	(1.02, 1.18)	(2.31, 2.56)

TABLE VI

COUNTERFACTUAL TARGETING SCENARIOS

Benefits relative to a random allocation for 300,000 NPR aid allocated to 38% of the population according to various targeting strategies – except universal scenario which uses 0.38*300,000 NPR allocated to the entire population. Bootstrapped 95% confidence intervals in parentheses using survey weights. Utilitarian refers to an 'equal-weighted' utilitarian social welfare function. Consumption and liquidity allocations based on households with the lowest values of those variables. Damages based on households with the highest self-reported earthquake damages. Shake Intensity based on villages with the highest peak-ground acceleration from USGS.

assuming that the amount of aid to each household is 0.38 x 300,000 = 114,000 NPR. Survey weights are used to make the estimates representative of the population in these districts. 95% confidence intervals for each targeting strategy are bootstrapped using 1,000 replicates, and reflect sampling error, but not specification error from the model or parameter estimates.

We find that the average household would give up 13.5% of future income in order to receive 300,000 NPR in reconstruction aid, reflecting a WTP of only 263,596 NPR in present value – slightly less than the nominal value of the aid.[11] There is substantial heterogeneity, however, with a standard deviation of nearly 150,000 NPR. If we restrict aid such that the household must invest all of it in their housing stock, the WTP for this type of conditional aid is on average 24% lower than for unconditional aid. If a planner was able to perfectly identify the households with the highest WTP for aid, this optimal allocation of aid would improve WTP by 52% relative to a random allocation.

[11]Present value calculation uses the estimated discount factor of 0.88.

We find that the WTP of households that actually received aid was 5% better than the random allocation. Since aid eligibility was conditional on the engineers assessments that the house was completely destroyed, this assessment should be considered to take in to account information about the the relative damages of the structure, but we also analyze a scenario based on targeting households with the largest absolute damages based on self-reports. We find that the welfare from this approach is similar to the true allocation – a 6% improvement over the random allocation. In column 3, we study a targeting policy that gives aid to all households in villages that experience the most intense shaking from the earthquake, whether or not their house was destroyed. Interestingly, this policy increases welfare by 8%, somewhat more than the actual allocation. None of these allocations perform well by the utilitarian criterion, however, all yielding substantially less welfare than the random allocation.

Columns 4 and 5 show the benefits of targeting the households with the lowest consumption and liquid wealth. These households are the typical targets of anti-poverty cash transfer programs, and unsurprisingly, targeting them performs well according to the utilitarian criterion. The welfare gains according to the WTP criterion are not significantly different from the random allocation, however, showing a clear tradeoff between the two welfare measures.

Finally, we analyze a universal aid allocation in column 6 that divides the aid budget among all the households in the sample. This approach does only marginally worse than the actual or damage based allocations by the WTP criterion, and this is before accounting for savings associated with targeting and administration of the allocation.[12] It far outperforms the actual and damage based allocations by the utilitarian criterion, though it does worse by this metric than targeting low-consumption or low-liquidity households.

The relative success of the universal approach reflects the concavity of household value functions over liquidity, implying diminishing WTP for aid. Giving all households a little bit of aid moves them up the steep section of their value functions. Intuitively, both the universal and the random allocation 'waste' some aid by giving it to households that don't

[12] Hanna and Olken (2018) argues the administration costs of targeting are typically low – on the order of 1% of the program budget, so this is not a huge source of gains. Given our estimates of the discount factor in Table IV, getting aid distributed more quickly could have been an additional source of welfare improvements, which is not accounted for in the estimates in this section.

need it. But the universal allocation makes sure that all households can cover some basic needs, while a random allocation may miss some very needy households, while giving larger amounts to less needy households.

One possible explanation for the relative success of the shake intensity and the universal targeting policies, neither of which conditions aid on housing damages, is that, as previously stated, our measure of WTP is not earthquake specific, and thus other types of shocks could influence household WTP. Table VII shows the average WTP for households that experienced different types of shocks, and the number of households that experienced each type of shock. The results show that on average, households experiencing the earthquake had higher WTP than households facing other types of shocks. This suggests that our results can be explained more due to heterogeneity in access to liquidity rather than the importance of other types of shocks.

These results show a clear tradeoff between policies that target households with high marginal utility for cash versus policies that target based on WTP for smoothing the shock. It is interesting to note, however, that the actual and damage based allocations are not best by either metric, though they are not strictly dominated either. A policy-maker interested in using aid to help households smooth consumption could have used the shake-intensity based allocation, which also has the virtue of being easier to observe, and thus, potentially quicker to deliver. A policymaker interested in using aid to help poor households should instead use traditional targeting approaches that target household with low levels of wealth and consumption.

	Average WTP	N Households
Earthquake	1.05	1,251
Drought and Other Disasters	1.00	53
Livestock Disease or Crop Failure	1.01	123
Riots	0.92	368
Illness or Injury in Household	0.96	567

TABLE VII

WILLINGNESS TO PAY FOR AID BY HOUSEHOLDS EXPERIENCING DIFFERENT TYPES OF SHOCKS (AS A FRACTION OF AVERAGE WTP).

5.1. *Sensitivity Analyses*

5.1.1. *Alternate Measures of Welfare*

As discussed in Section 3, an alternative to measuring WTP based on permanent income estimated in the period when aid is delivered, is to measure WTP based on either pre-earthquake permanent income, or post-aid permanent income. This is simply to compute, since we have already estimated τ_i, we simply need to adjust equation 3 with the relevant estimate of P_{it}.

Using pre-earthquake income could be important if exposure to the disaster has a durable negative effect on incomes. We do not observe pre-disaster incomes, but in Appendix C, we regress household damages on income, using shake intensity as an instrument, and we find that, if anything, incomes are higher in earthquake exposed households, even in the first wave of the survey, before households had received aid. Still, as a best-case scenario for damage-based targeting, we test robustness to the assumption that households with earthquake-related housing damages had pre-quake incomes 10% higher than we estimate.

In this case, both the actual and the damage-based targeting scenarios perform better, increasing welfare by 9% and 10% relative to the random allocation respectively. Targeting based on shake intensity does equally well, if not better, increasing welfare by 10% relative to the random allocation. The universal scenario still increases welfare by 4%. See Appendix D for full results.

We also consider using post-aid permanent income. While the regression discontinuity analysis doesn't find robust effects on income, the point estimates are large and noisy. Applying a 0.93 log point increase in incomes to all households doesn't change the relative welfare of targeting schemes at all, but it does change the magnitude of estimated WTP to 674,218 NPR, now more than double the nominal value of the aid. Heterogeneity in income effects could change the relative rankings of various targeting schemes, but it may be less likely that the households that need to spend the aid rebuilding their homes will also have access to more profitable investment opportunities.

5.1.2. *Alternate Parameters*

Since our estimates of the coefficient of risk aversion ($\gamma = 4.46$) and discount factor (0.88) indicate quite strong present bias and risk aversion relative to previous estimates in the literature, we test the sensitivity of our results to these parameters, instead using the Kaboski and Townsend (2011) values of $\gamma = 1.2$ and $\beta = 0.926$. In particular, a large coefficient of risk aversion indicates a steep utility function at low levels of wealth and rapidly diminishing WTP for aid. This makes universal targeting a relatively more attractive strategy, since a smaller cash distribution, given to everyone, can ensure that all households move out of this steep section of the utility function. Table D.I in Appendix D confirms this result. Using the lower coefficient of risk aversion decreases the relative benefits of universal aid by 2% and increases the benefits of the actual, damage based, and shake-intensity based allocation by 1% each.

Given the lack of previous estimates in the literature of the minimum housing stock parameter $\bar{h}$, we also study sensitivity to this parameter, setting it to 0.095, one-tenth of our previous estimate. This increases the relative benefits of the actual, damage-based, and shake-intensity allocations to 9-10% better than the random allocation. This is unsurprising, as reducing the value of the outside option for housing increases the value of targeting households with housing damages. Interestingly, however, targeting low-liquidity households and universal aid also perform well in this scenario, with benefits of 9% and 7% relative to the random allocation respectively. Intuitively, the lower value of $\bar{h}$ makes the value function steeper, in some ways mimicking the effects of a higher risk-aversion parameter. Full results are in Appendix D.

5.1.3. *Different Distributions of State Variables*

Lastly, we perform a simple exercise to study how our results depend on the specific distributions of state variables in this context. We adjust all three state variables (x_{it}, h_{it}, P_{it}) according to $s_{it} = w(s_{it} - \bar{s}) + gs_{it}$, where s is a state variable, w controls the spread of the distribution (with mean $\bar{s}$) and g controls the mean of the distribution. For each distribution, we calculate the ratio of aggregate welfare from the actual targeting policy to the welfare under the universal allocation. Full results are in Appendix D.

The universal allocation tends to be better when inequality is low. With $g = 1$ and $w = 0.5$, the targeting policy creates 7.3% less welfare than universal aid, whereas with $w = 2$, targeting creates 3.6% more welfare. The effect of g is more ambiguous. Holding $w = 1$, and increasing g from 1 to 2 makes virtually no difference, the relative benefits of targeting slightly decrease from 1.6% to 0.5%. When $w = 2$, however, the relative benefits of targeting are 7% greater when $g = 2$. Targeting is more important in a richer, more unequal context.

6. CONCLUSION

Natural disasters may present households with shocks that existing institutional arrangements are incapable of smoothing. This is especially likely when the disaster is outside of recent lived experience, and when the disaster occurs in a low-income country, where credit constraints are more likely to bind and informal risk sharing networks can be overwhelmed by a large covariate shock. In these circumstances, aid can facilitate reconstruction and consumption smoothing by providing liquidity to ease these constraints.

Targeting aid could be important, if households differ in their value for aid, and good proxies for these values are available to those in charge of distribution. We find that targeting modestly increased the value of aid in this setting, although targeting villages with the highest shake intensity would have done better. This strategy has the additional benefit of not requiring any budget or time for conducting a needs assessment. We also found that damage-based allocations do not perform well by a utilitarian criterion, which prioritizes low-wealth, low-consumption households.

Several factors might affect the external validity of these conclusions. An earthquake is a particular type of disaster, in that the main effect is usually to destroy structures, which may be a less important input into production in a rural agricultural setting. Endogenizing the income process could be more important to analyze flooding or droughts, or targeting aid in an urban setting, and should be considered in future research. Second, the aid program analyzed here was delivered more than a year after the disaster. Although this time frame may be typical for reconstruction aid, the implications for targeting emergency relief in the immediate aftermath of a disaster could differ, especially when aid is in the form of in-kind goods rather than cash. Finally, analyzing the optimal amount of targeting likely depends upon the existence of other social insurance programs, which would be more important in wealthy and middle-income countries.

There are other potential downsides to allocating aid based on damages that are beyond the scope of this paper, but could be examined in future work. Aid that is conditional on property damage might create perverse incentives if property owners fail to internalize the full risks of building in disaster-prone areas, or under-invest in hazard mitigation more generally. This is probably unlikely for a once-a-century earthquake in a country without major social insurance programs, but more plausible for recurrent disasters and more experience with post-disaster aid programs.

Furthermore, as mentioned in Section 2, disputes over beneficiary lists led to protests and delays. Given the importance of speed in aid delivery, more research should address the political economy concerns of targeting, and what types of allocations are easiest to administer. One possible explanation for the popularity of damage-based aid is that the eligibility criteria should be relatively transparent and easy to administer. This did not seem to be the case in Nepal, however (The Asia Foundation, 2016*b*). Given these results, it is important to study whether alternative allocation mechanisms, including community-based or universal approaches, would have been perceived as more fair by those that lived through the disaster.

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ONLINE APPENDIX: TARGETING DISASTER AID: A STRUCTURAL EVALUATION OF A LARGE EARTHQUAKE RECONSTRUCTION PROGRAM

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APPENDIX A: APPENDIX A. STRUCTURAL MODEL AND ESTIMATION

A.1. *Value Function Normalization*

Define $X_{it}, H_{it}, C_{it}, I_{it}, Y_{it}$ as the true values of wealth, housing, consumption, housing investment, and income respectively, with $x_{it}, h_{it}, c_{it}, \iota_{it}, y_{it}$ as the same variables normalized by $E(Y_{it}) = P_{it} = exp(\mu_{it} + \sigma^2/2)$. From equation (5) we have:

$$U_i = E[\sum_{t=0}^{\infty} \beta^t \frac{C_{it}^{\alpha} H_{it}^{1-\alpha}{}^{(1-\gamma)}}{1-\gamma}] \tag{15}$$

$$= E[\sum_{t=0}^{\infty} \beta^t \frac{\left((P_{it}c_{it})^{\alpha}(P_{it}h_{it})\right)^{(1-\alpha)}{}^{(1-\gamma)}}{1-\gamma}]$$

$$= P_{it}^{1-\gamma} E[\sum_{t=0}^{\infty} \beta^t \frac{c_{it}^{\alpha} h_{it}^{1-\alpha}{}^{(1-\gamma)}}{1-\gamma}].$$

Thus if ν is the value function associated with maximizing $E[\sum_{t=0}^{\infty} \beta^t u(c_{it}, h_{it})]$, $V_i = P_{it}^{1-\gamma}\nu$ is the value function associated with maximizing equation (5). The normalization carries through to all the state variables without issue, observing that $log(y_{it}) = log(Y_{it}/P_{it}) = log(Y_{it}) - log(P_{it}) = log(Y_{it}) - \mu_{it} - \frac{\sigma^2}{2} \sim N(-\frac{\sigma^2}{2}, \sigma^2)$.

Therefore, we solve for:

$$P_{it}^{\gamma-1} V(x_{it}, h_{it}|P_{it}) = \nu(x_{it}, h_{it}) = \max_{d_i} \Bigg\{ \tag{16}$$

$$d_i \Big[u(\bar{c}, \max[h_{it}, \bar{h}], 0) + \beta E\big[\nu\big(R\lambda + y_{it+1}, \delta \max[h_{it}, \bar{h}]\big)\big]\Big],$$

$$(1-d_i)\Big[\max_{c_{it}, \iota_{it}} u(c_{it}, h_{it}, \iota_{it}) + \beta E\big[\nu\big(R(x_{it} - c_{it} - \iota_{it}) + y_{it+1}, \delta h_{it} + \iota_{it+1}\big)\big]\Big] \Bigg\}$$

subject to the constraints:

$$x_{it} - c_{it} - \iota_{it} \geq \lambda \tag{17}$$

$$\iota_{it} \geq 0. \tag{18}$$

and the corresponding optimal consumption and investment functions.

The closed form expression for τ comes the definition of τ as:

$$\begin{aligned} V_i(x_{it}, h_{it}, P_{it}) &= V_i(x_{it} + a, h_{it}, (1 - \tau_{it})P_{it}) \\ P_{it}^{1-\gamma}\nu_i(x_{it}, h_{it}) &= P_{it}^{1-\gamma}(1-\tau)^{1-\gamma}\nu_i(x_{it} + a, h_{it}) \\ \frac{\nu_i(x_{it}, h_{it})}{\nu_i(x_{it} + a, h_{it})} &= (1-\tau)^{1-\gamma} \\ \tau &= 1 - \left[\frac{\nu_i(x_{it} + a, h_{it})}{\nu_i(x_{it}, h_{it})}\right]^{1/(\gamma-1)} \end{aligned} \tag{19}$$

Since the value function is negative everywhere and bounded by 0, the ratio is < 1, and the ratio is decreasing in in the increase in utility from aid, so τ is increasing.

A.2. *Finding the Policy Functions*

It is possible to solve for the value function and optimal policy functions, $c^*(x, h, P)$, $\iota^*(x, h, P)$, and $d^*(x, h, P)$, given a set of parameters using Value Function Iteration (VFI). We start with the guess that the value function is equal to zero everywhere. The value function is stored in a grid of 1600 points, with 40 equally-spaced points in both the x and h dimensions. We interpolate the value function between grid points using the multidimensional simplical scheme described in Judd (1998). The income process is discretized by exponentiating 30 Gaussian quadrature points. At each grid point we find the values of c and ι that maximize A1. Since the default decision introduces a kink in the value function, which can lead to local minima in the objective function resulting from the approximation and interpolation scheme, we use a semi-global optimization algorithm at each grid point(Gablonsky and Kelley, 2001, Johnson, 2022).

The value of the objective function at the maximum is then stored as ν_2. Thus, for each subsequent iteration n+1, we solve for:

$$\nu_{n+1} = \max u(c_t, h_t) + \beta E[\nu_n(x_{t+1}, h_{t+1})]. \tag{20}$$

This is repeated until the relative mean squared difference in $c^*(x, h)$ between iterations is less than .0025.

A.3. *Parameter Estimation*

The parameter vector is estimated by minimizing the MSM objective function using a set of 17 moment conditions derived from the model described below. To do so we use a nested fixed-point algorithm: the outer loop iterates over parameters, while the inner loop estimates the optimal policy functions at each set of parameters.

Since approximation errors in the inner loop can generate local minima in the objective function, we first search for an approximate global minima of equation (21) using the DIRECT global optimization algorithm (Powell, 1998). We use that minima to estimate the optimal weighting matrix, W (Hansen, 1982), and also use it as the starting point of a local optimization algorithm in a final iteration to estimate the parameter vector ($\hat{\theta}$) to satisfy:

$$\begin{aligned}\hat{\theta} = \arg\min_{\theta}\Big(\sum_{i=1}^{N}\sum_{t=2}^{3}\sqrt{w_i}g_{it}(\theta, x_{it}, h_{it}, P_{it}, \iota_{it}, c_{it}, d_{it}, y_{it})\Big)^T\widehat{W} \\ \Big(\sum_{i=1}^{N}\sum_{t=2}^{3}\sqrt{w_i}g_{it}(\theta, x_{it}, h_{it}, P_{it}, \iota_{it}, c_{it}, d_{it}, y_{it})\Big).\end{aligned} \tag{21}$$

Where $g_{it} = \{e_{it1}, ..., e_{it17}\}^T$, w_i are the survey weights, and $\widehat{W}$ is the inverse of the estimated covariance matrix of moments from the first stage optimization. The first survey wave is dropped because lagged cash savings and lagged housing value are needed to construct the state variables.

A.3.1. *Moment Conditions*

The optimal policy functions for consumption, investment, and default define the first three moment conditions:

$$\begin{aligned} e_{it1} &= c^*(x_{it}, h_{it}, M_i) - c_{it} \\ e_{it2} &= \iota^*(x_{it}, h_{it}, M_i) - \iota_{it} \\ e_{it3} &= d^*(x_{it}, h_{it}, M_i) - d_{it}. \end{aligned} \tag{22}$$

Following Kaboski and Townsend (2011), we gain six additional moment conditions by interacting e_1 and e_2 with transformations of each of the state variables. Intuitively, this helps ensure that the model's predictions are not biased in expectation for any values of the state variables:

$$
\begin{aligned}
e_{it4} &= e_{it1}\log(M_i) \\
e_{it5} &= e_{it1}\ \text{ihs}(x_{it}) \\
e_{it6} &= e_{it1}\log(h_{it}+1) \\
e_{it7} &= e_{it2}\log(M_i) \\
e_{it8} &= e_{it2}\ \text{ihs}(x_{it}) \\
e_{it9} &= e_{it2}\log(h_{it}+1).
\end{aligned}
$$

The inverse hyperbolic sine function is used for x_{it} to handle negative values.

Moment conditions 10-12 help to pin down interest rates by using data on household capital income and loan payments made and received.

$$
\begin{aligned}
e_{it10} &= (R-1)\textit{Cash Savings}_{it} - \textit{Capital Gains}_{it} \\
e_{it11} &= \sum_{T=1}^{3}\frac{R^T(R-1)}{R^T-1}\textit{Loans Taken}_{it} - \textit{Loan Payments Made}_{it} \\
e_{it12} &= \sum_{T=1}^{3}\frac{R^T(R-1)}{R^T-1}\textit{Loans Made}_{it} - \textit{Loan Payments Received}_{it}
\end{aligned}
$$

T is the term of the loan. We use any outstanding consumption (non-investment) loans in period t with a 3 year term or less.

The next moment condition helps to pin down depreciation rates based on a hedonic approach using the age of the home. Consider the regression with household and year fixed effects:

$$
\begin{aligned}
\log(\textit{Housing Value}_{it}) = & a_1 \textit{Age of Home}_{it} + \\
& a_2 \textit{Housing Investment}_{it} + \eta_i + \phi_t + e_{it}.
\end{aligned} \tag{23}
$$

The coefficient $a_1 = \delta - 1$ in the model. We can use the Frisch-Waugh-Lovell theorem to derive an appropriate moment condition based on this regression:

$$e_{it13} = \widetilde{\mathit{Age\ of\ Home}}_{it}\Big(\widetilde{\mathit{Housing\ Value}}_{it} - (\delta-1)\widetilde{\mathit{Age\ of\ Home}}_{it}\Big).$$

where $\widetilde{\mathit{Housing\ Value}}_{it}$ and $\widetilde{\mathit{Age\ of\ Home}}_{it}$ are the residuals of a regression of those variables on housing investment and the household and survey year fixed effects. Table B.IV shows estimates of equation 23, as well as robustness of the estimates to other specifications.

The final two moment conditions helps identify the variance of the income process and measurement error. We multiply $P_{it}s_{it}$, where s_{it} is a measurement error shock drawn i.i.d from $\log(s_{it}) \sim N(\frac{\sigma_m^2}{2}, \sigma_m^2)$. This distribution ensures that for any choice or state variable $Z_{it}, E(\frac{Z_{it}}{P_{it}s_{it}}) = \frac{Z_{it}}{P_{it}}E(1/s_{it}) = \frac{Z_{it}}{P_{it}}e^{-\frac{\sigma_m^2}{2}+\frac{\sigma_m^2}{2}} = \frac{Z_{it}}{P_{it}}$, so all previous moment conditions remain valid in their normalized form.

Then $\log(\tilde{y}_{it}) := \log(Y_{it}/(P_{it}s_{it})) \sim N(-\frac{\sigma^2}{2} - \frac{\sigma_m^2}{2}, \sigma^2 + \sigma_m^2)$. Therefore we use the following moment conditions:

$$e_{it14} = \log(\tilde{y}_{it}) + \frac{\sigma^2}{2} + \frac{\sigma_m^2}{2}$$
$$e_{it15} = \log(\tilde{y}_{it})^2 - \Big(\frac{\sigma^2}{2} + \frac{\sigma_m^2}{2}\Big)^2 - \sigma^2 - \sigma_m^2.$$

All moment conditions are normalized by dividing by the average value of the relevant variable in the data (e.g. average consumption, investment, default, etc...). We estimate these moments using 11,115 household-year observations from the second and third waves – we also drop approximately 5% of households that did not answer large portions of the survey, making the construction of key variables impossible. For households that answered 'Don't Know' for certain rare types of income, especially capital gains, we impute a zero for that category of income.

A.3.2. *Purging Lifecycle Variation and Household Heterogeneity*

Since the data contain variation not explicitly modelled, including life-cycle considerations and other unobserved determinants of household heterogeneity, we follow the buffer stock literature in purging these sources of variation from the estimation procedure (Kaboski and Townsend, 2011). This procedure is necessary to ensure that household values for aid are not biased by life cycle considerations, household size, or other systematic differences between households. Consumption and savings patterns may differ between older and younger families, for example, even if they had the same values for aid. Purging variation associated with these differences requires careful consideration, however, since our counterfactuals address targeting, the value of which depends on household heterogeneity.

To be precise, our model says that households are only heterogeneous in their history of shocks to income and housing stock – including the earthquake – and their expected income, and we seek to understand how this heterogeneity correlates with different targeting programs.

If a targeting program correlates with any of the exogenous characteristics purged from the data, then removing that source of variation will remove any value created (or destroyed) by systematically targeting those households. Thus purging regional variation, for example, is undesirable, since earthquake damages vary across space, and a targeting program might want to take that into account.

On the other hand, the age structure of the household, household size (including migrant members), and education can be plausibly seen as exogenous to the earthquake damages, as well as the targeting strategies under consideration, yet may account for systematic differences in behavior. Survey fixed effects are included to capture macroeconomic fluctuations - including price changes and exchange rates.

Purging these sources of variation results in a nuanced interpretation of household values for aid. The estimates reflect household value for aid conditional on the set of exogenous household characteristics. This is consistent with the idea that aid is to be used for smoothing welfare through the disaster, and not redistributing between different types of households.

Thus we run the following regressions:

$$\begin{aligned} log(C_{it}+1) &= \Gamma_1 W_{it} + \epsilon^1_{it} \\ log(H_{it}+1) &= \Gamma_2 W_{it} + \epsilon^2_{it} \\ d_{it} &= \Gamma_3 W_{it} + \epsilon^3_{it} \\ X_{it} &= \Gamma_4 W_{it} + \epsilon^4_{it} \end{aligned} \tag{24}$$

Where W_{it} is a vector of household characteristics containing quadratic polynomials of age of the head of household, education, and the number of members (including migrants), as well as the number of children and elderly members, and survey wave fixed effects. We add one to consumption and housing to maintain households with a zero value for those variables, since these households could be particularly valuable from a targeting perspective. The R squared values of these regressions are .32, .07, .08, and .01 respectively.

We then construct an adjusted dataset, where the values of consumption, housing wealth, default, and liquidity are the fitted values of 24 for a household with mean values of the independent variables, plus the household specific residual. For example, adjusted household consumption is constructed as:

$$\tilde{C}_{it} = \exp(\widehat{\Gamma}_1 \bar{W}_{it} + \widehat{\epsilon}^1_{it}). \tag{25}$$

Income is treated similarly, but we also allow for additional household heterogeneity in order to more accurately estimate expected income. We include a vector of additional characteristics, U_{it}, which includes the value of household landholdings, the gender of the head of household, the number and destination of previous migrants, migrant earnings, ethnicity and village fixed effects. The R squared of the income regression with these additional characteristics is .24. We then construct expected income and income shocks as follows:

$$log(Y_{it}+1) = \Gamma_5 W_{it} + \omega U_{it} + \epsilon^5_{it} \tag{26}$$

$$\tilde{Y}_{it} = \exp(\widehat{\Gamma}_5 \bar{W}_{it} + \widehat{\omega} U_{it} + \widehat{\epsilon}^5_{it}) \tag{27}$$

$$M_{it} = \exp(\widehat{\Gamma}_5 \bar{W}_{it} + \widehat{\omega} U_{it}) \widehat{\xi}_t \tag{28}$$

Where $\widehat{\xi}_t = \sum_i w_i \exp(\widehat{\epsilon}^5_{it})$ is the weighted smear factor used to retransform the expected income values back to the scale of the original variable (Duan, 1983). The adjusted values of consumption, housing, default, liquidity, and income are all also multiplied by a common factor to ensure that their means in the adjusted data are the same as in the original data. Lastly, housing investment is adjusted by multiplying housing investment in the data by the ratio of adjusted income to unadjusted income. The adjusted data is then used to both estimate the parameters and conduct counterfactuals.

All code is written in R and is available from:
https://github.com/mdgordo/nepal_earthquake/.

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APPENDIX B: APPENDIX B. ADDITIONAL FIGURES AND TABLES

B.1. *Timeline and Summary Statistics*

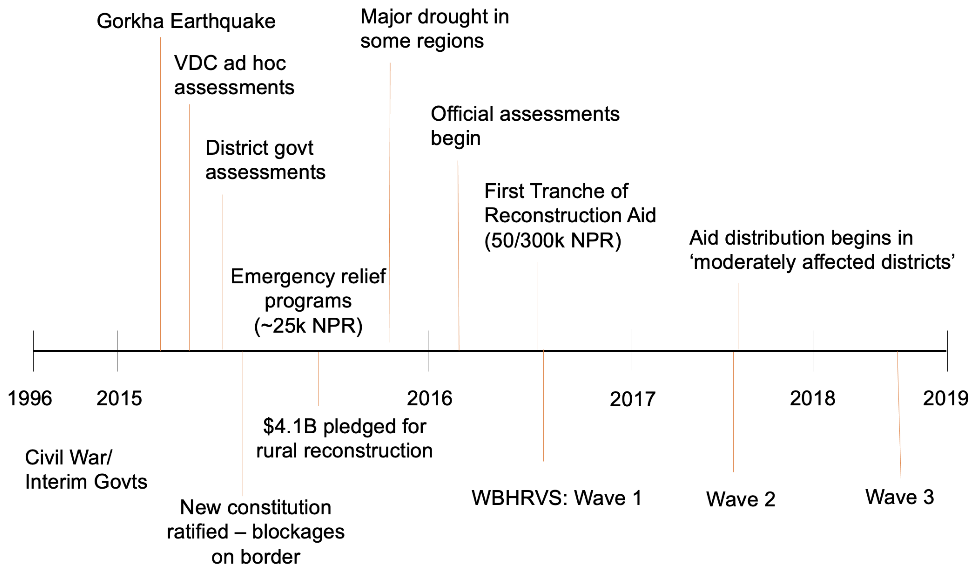

FIGURE B.1.—Timeline of Events

Statistic	N	Mean	Std.Dev.	Min	Max
Consumption	17,782	153,227	89,471	10,838	3,908,772
Food Consumption	17,782	114,077	60,864	1,560	938,704
Income	17,782	275,265	1,831,704	196	220,557,220
Productive Assets	17,779	1,946,683	10,007,589	0	809,395,500
Investments	17,780	39,110	284,253	0	15,000,000
Jewelery	17,742	73,040	174,598	0	12,500,000
School Costs	17,773	14,941	43,174	0	4,477,000
Home Value	17,781	1,228,095	2,232,228	0	70,000,000
Home Investment	17,782	23,083	154,747	0	10,500,000
Age of House	17,782	15.3	13.6	0	122
Household Members	17,478	4.66	1.97	1	21
Connected Migrants	17,782	0.77	1.19	0	18
Migrants Past Year	17,782	0.23	0.63	0	11
Overseas Migrants	17,782	0.40	0.71	0	8
Female Headed(%)	17,478	0.21	0.41	0	1
Cash Savings	17,708	50,444	160,758	0	5,015,000
Remittance Income	17,782	63,000	164,267	0	5,000,000
Loans Taken Past Year	17,768	28,726	123,351	0	7,000,000
Loans Made Past Year	17,782	2,198	26,278	0	1,500,000
Default(%)	17,757	0.19	0.40	0	1
Skipped Meal(%)	17,782	0.10	0.31	0	1
Earthquake Aid	17,782	18,440	74,826	0	2,182,000
Earthquake Aid(%)	17,782	0.13	0.37	0	1
NGO Aid	17,782	830	15,405	0	700,000
Public Transfers	17,736	4,482	10,875	0	320,500
Informal Transfers	17,782	2,571	22,804	0	2,807,540
Earthquake Losses (%)	17,782	0.21	0.43	0	1
Earthquake Losses	17,782	47,436	200,454	0	4,000,000

TABLE B.I

SUMMARY STATISTICS

Consumption includes value of all food consumption, energy, utilities, transportation and miscellaneous purchases, but not durables. Income is the sum of wages, rental income, agriculture and livestock sales, home food production, business revenues, pension and other public welfare. It does not include remittances or transfers. Productive Assets are the sum of the value of land, agricultural equipment, and livestock. Investments include land purchased, business investments, livestock purchases or farm equipment purchases. Cash savings includes cash on hand and bank savings plus insurance and savings group assets. Loans reflect short term credit (three years or less). Survey weights are used to calculate means and standard deviations. N is non-missing household-year observations in the three year panel.

	log(consumption)				
	(1)	(2)	(3)	(4)	(5)
log(income)	0.107***	0.113***	0.106***	0.116***	0.104***
	(0.012)	(0.017)	(0.012)	(0.010)	(0.011)
log(income):Dalit		−0.017			
		(0.024)			
log(income):Newar		−0.053*			
		(0.028)			
log(income):Other		−0.005			
		(0.017)			
log(income):Female Head			−0.010***		
			(0.002)		
log(income):Land > Median				−0.018***	
				(0.005)	
log(income):Quake Affected					0.015
					(0.019)
Observations	16 742	16 741	16 742	16 742	16 742
R2	0.727	0.727	0.728	0.727	0.727

TABLE B.II

CONSUMPTION SMOOTHING: CASTE YEAR FIXED EFFECTS

All regressions include household and caste-year fixed effects. Standard errors clustered at the survey strata. Observations with zero or missing income, or less than 3 observations dropped. Land percentile defined based on household land value during first survey wave. Omitted category for caste is "Brahmin/Chhetri". * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	log(consumption)				
	(1)	(2)	(3)	(4)	(5)
fit log(income)	0.274***	0.217***	0.271***	0.272***	0.271***
	(0.018)	(0.023)	(0.017)	(0.024)	(0.020)
fit log(income):Dalit		0.082***			
		(0.024)			
fit log(income):Newar		−0.041			
		(0.065)			
fit log(income):Other		0.076***			
		(0.020)			
fit log(income):Female Head			0.000		
			(0.002)		
fit log(income):Land > Median				−0.012	
				(0.035)	
fit log(income):Quake Affected					−0.194***
					(0.037)
Observations	16 742	16 741	16 742	16 742	16 742
R2	0.653	0.656	0.655	0.658	0.664

TABLE B.III

CONSUMPTION SMOOTHING: RAINFALL INSTRUMENTS

All regressions include household fixed effects, and instrument for income using total rainfall in each of the preceding 12 months. Rainfall data comes from Funk et al. (2015). Standard errors clustered at the household. Observations with zero or missing income, or less than 3 observations dropped. Land percentile defined based on household land value during first survey wave. Omitted category for caste is "Brahmin/Chhetri". * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	log(house value)	log (house value + 1)	house value	log(house value)	log (house value + 1)	house value	log(house value)	log (house value + 1)	house value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Age of House	−0.020***	−0.022***	−0.018***	−0.017***	−0.017**	−0.018***	−0.015**	−0.016**	−0.015***
	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Home Investment				0.000	0.000	0.000	0.000	0.000	0.000
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	16 591	16 742	16 742	16 591	16 742	16 742	16 591	16 742	16 742
R2	0.700	0.531		0.701	0.532		0.716	0.544	
Estimator	OLS	OLS	Poisson	OLS	OLS	Poisson	OLS	OLS	Poisson
Year FEs	X	X	X	X	X	X			
Linear Time Trend							X	X	X
District*Year FEs							X	X	X

TABLE B.IV

HOUSING DEPRECIATION: HEDONIC REGRESSIONS

Coefficients of OLS and Poisson regression analogs of the housing depreciation moment condition described in Appendix A. Columns differ in the fixed effects included and whether the dependent variable is log house value (with zeros dropped) or log house value + 1 in the OLS specifications, or house value for the poisson specifications. All regressions have household fixed effects and standard errors clustered at the survey strata. Households with less than 3 observations dropped. Column 5 is the basis of the moment condition estimated using MSM. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B.2. *Regression Discontinuity Plots and Tables*

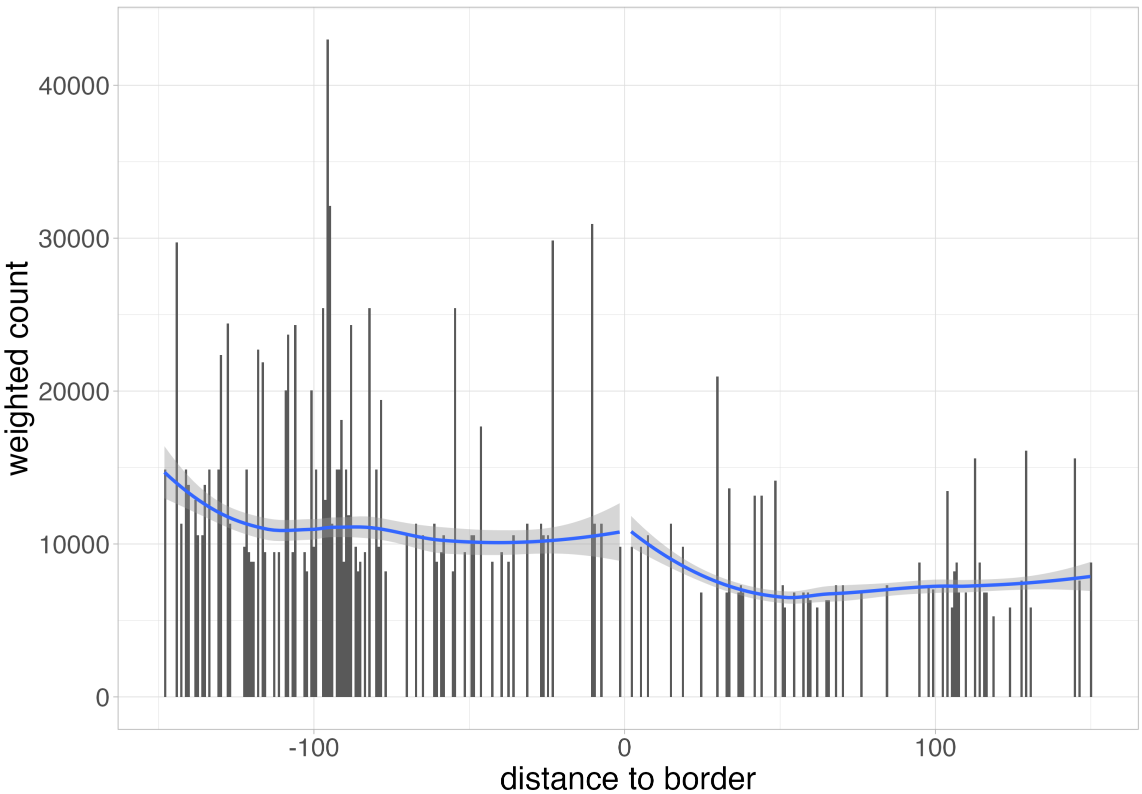

FIGURE B.2.—McCrary Test: Weighted density of households on either side of the border with smoothed means.

	Received Aid	Aid Amount	Received Aid	Aid Amount	Received Aid	Aid Amount	Received Aid	Aid Amount	Received Aid	Aid Amount	Received Aid	Aid Amount
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Distance > 0	0.23***	39,750***	0.18***	38,076***	0.17***	38,661***	0.27***	42,113***	0.53***	48,610***	0.26***	56,044***
	(0.07)	(7,138)	(0.06)	(8,772)	(0.06)	(8,699)	(0.07)	(7,552)	(0.10)	(10,325)	(0.08)	(12,247)
N	1093	2449	1485	1006	1357	1051	784	1881	476	608	1053	1009
Bandwidth	35.43	62.13	43.01	33.56	40.2	33.77	28.53	50.97	20.39	23.57	36.5	35.7
Kernel	triangular	triangular	triangular	triangular	triangular	triangular	epanechnikov	epanechnikov	uniform	uniform	triangular	triangular
Controls			Damages	Damages	Damages/Geo/Demo	Damages/Geo/Demo						
Exclude unaffected Dists.												
5 km Donut											X	X
Border	Western	Western	Western	Western	Western	Western	Western	Western	Western	Western	Western	Western
Wards	57	87	66	39	59	39	37	70	32	52	64	49

	Received Aid	Aid Amount	Received Aid	Aid Amount	Received Aid	Aid Amount	Received Aid	Aid Amount	Received Aid	Aid Amount	Received Aid	Aid Amount
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Distance > 0	0.44***	42,112***	0.22***	39,354***	0.29***	40,542***	0.24***	39,688***	0.24***	16,635***	0.22***	12,550***
	(0.10)	(11,293)	(0.06)	(8,292)	(0.05)	(7,224)	(0.07)	(7,146)	(0.05)	(3,885)	(0.05)	(3,729)
N	476	476	1357	1357	2360	2360	1093	2404	1580	3026	1450	3290
Bandwidth	20	20	40	40	60	60	34.66	62.07	10.55	23.65	10.41	24.64
Kernel	triangular	triangular	triangular	triangular	triangular	triangular	triangular	triangular	triangular	triangular	triangular	triangular
Controls											Damages/Geo/Demo	Damages/Geo/Demo
Exclude unaffected Dists.							X	X				
5 km Donut												
Border	Western	Western	Western	Western	Western	Western	Western	Western	Whole	Whole	Whole	Whole
Wards	11	11	32	32	56	56	54	81	65	112	65	115

	Received Aid	Aid Amount	Received Aid	Aid Amount	Received Aid	Aid Amount	Received Aid	Aid Amount	Received Aid	Aid Amount
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Distance > 0	0.41***	62,630***	0.33***	89,547***	0.36***	88,240***	0.78***	45,729***	0.92	100,959***
	(0.09)	(18,672)	(0.08)	(28,797)	(0.07)	(28,087)	(0.15)	(13,650)	(656,518)	(28,846)
N	1047	566	1355	215	1660	215	171	1181	126	215
Bandwidth	40.86	34.7	47.72	22.29	52	22.59	19.84	42.57	15.33	23.18
Kernel	triangular	triangular	triangular	triangular	triangular	triangular	epanechnikov	epanechnikov	uniform	uniform
Controls			Damages	Damages	Damages/Geo/Demo	Damages/Geo/Demo				
Exclude unaffected Dists.										
5 km Donut										
Border	Close Point	Close Point	Close Point	Close Point	Close Point	Close Point	Close Point	Close Point	Close Point	Close Point
Wards	57	61	64	32	69	34	32	70	21	57

	Received Aid	Aid Amount	Received Aid	Aid Amount	Received Aid	Aid Amount	Received Aid	Aid Amount	Received Aid	Aid Amount
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Distance > 0	0.59***	71,027***	0.42***	52,012***	0.42***	44,312***	3.76***	66,627***	0.41***	57,931***
	(0.11)	(19,821)	(0.10)	(15,376)	(0.07)	(11,215)	(0.59)	(19,863)	(0.09)	(17,357)
N	479	479	960	960	1880	1880	173	479	1047	829
Bandwidth	30	30	40	40	60	60	22.62	33.3	41.14	37.67
Kernel	triangular	triangular	triangular	triangular	triangular	triangular	triangular	triangular	triangular	triangular
Controls										
Exclude unaffected Dists.									X	X
5 km Donut							X	X		
Border	Close Point	Close Point	Close Point	Close Point	Close Point	Close Point	Close Point	Close Point	Close Point	Close Point
Wards	11	11	23	23	45	45	44	57	56	63

TABLE B.V

FIRST STAGE REGRESSION DISCONTINUITY

Local linear regressions with triangular kernel x survey weights, heteroskedasticity-robust standard errors. Slope of running variable allowed to differ on either side of cutoff. Full set of control variables for Damages/Geo/Demo specifications includes self-reported earthquake, age and education of household head, a dummy for high caste, and the travel time to nearest health clinic. 'Close Point' refers to specifications where the running variable is distance to the specific point on the border that is closest to any village. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels respectively.

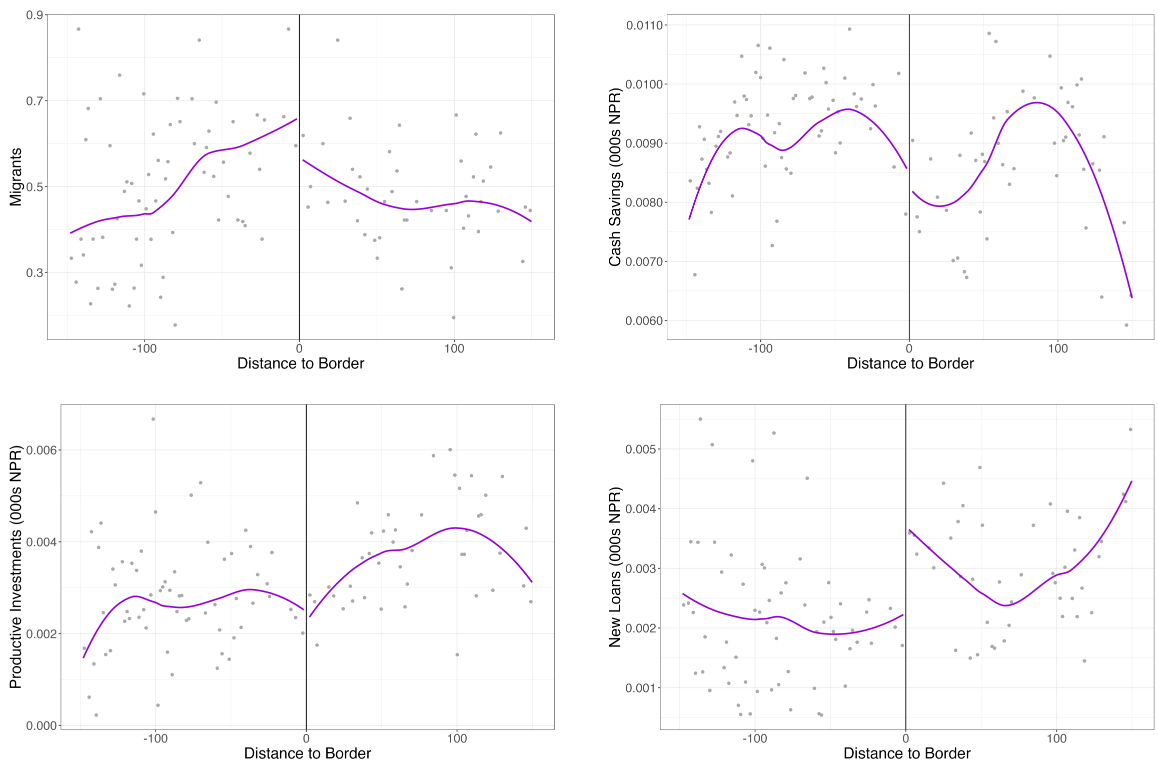

FIGURE B.3.—RD Plots: Binned averages of migrations, cash savings, productive investments and loans taken in the past year as a function of distance to the border with Loess smoothing. Positive values indicate villages inside the districts that were prioritized for aid.

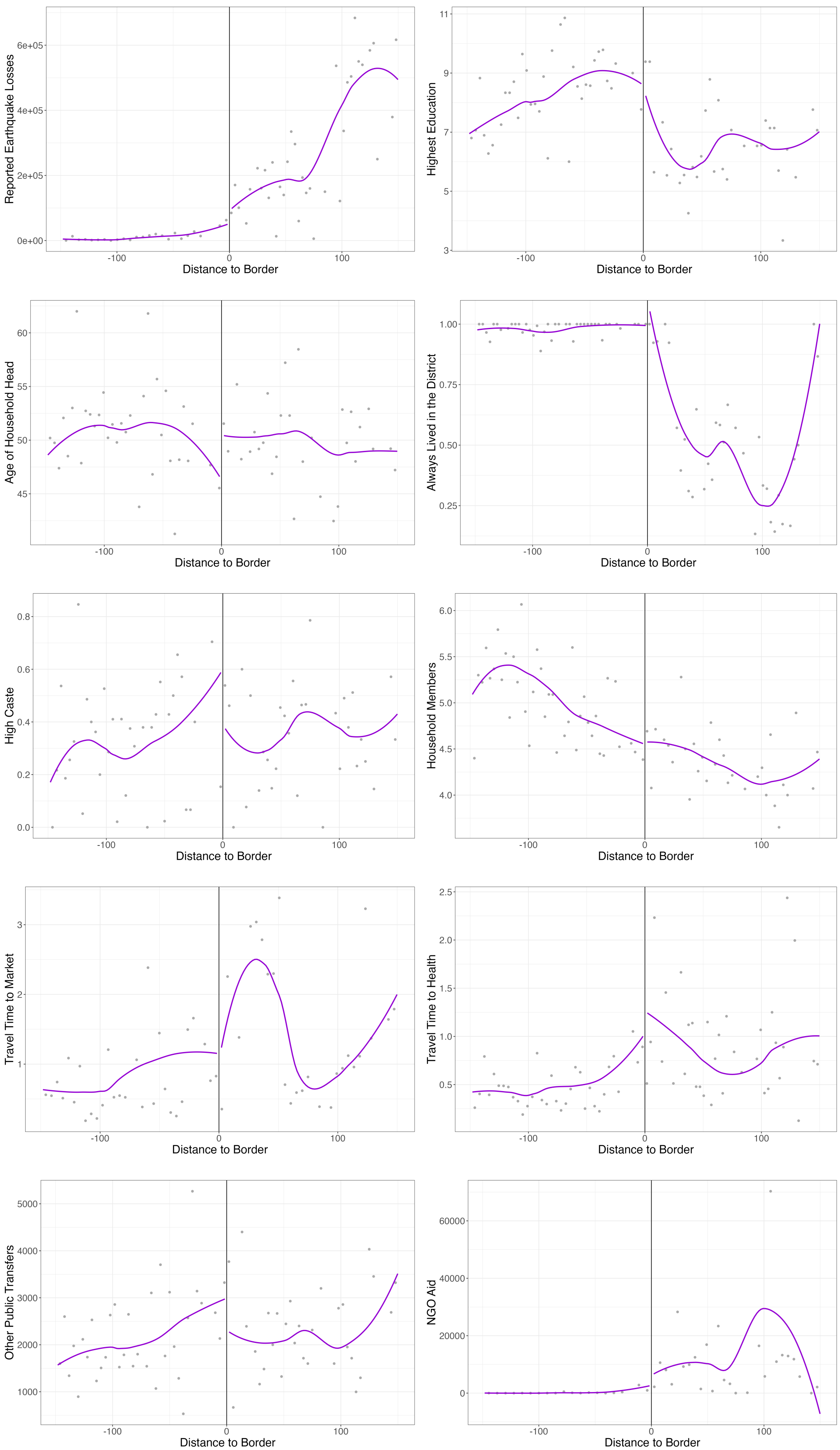

FIGURE B.4.—RD Plots: Binned averages of placebo variables from first survey wave as a function of distance to the border with Loess smoothing. Positive values indicate villages inside the districts that were prioritized for aid.

Running Variable: Distance to Border (Main Specification)

	gorkha loss ever	high caste	age hh	highest ed	hhmembers	class5	class10	always lived house	always lived dist	NGO transfers	non quake aid
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$\widehat{Aid}$	222,734	-1.55	32.90	1.92	0.77	-0.01	0.96	0.53	0.53	17,545	$-1,183$
	(167,669)	(1.44)	(33.93)	(5.59)	(2.61)	(0.47)	(1.09)	(0.46)	(0.46)	(14,561)	(9,049)
N	505	437	422	408	408	605	437	422	422	351	437
Bandwidth	44.05	41.72	39.06	37.41	37.39	50.75	41.23	39.18	39.18	34.38	39.62
Wards	57	60	60	62	48	64	55	62	62	41	61

	chicken price	rice price	lentil price	sugar price	mutton price	time to school	time to health	time to market	time to bank	slope	elevation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$\widehat{Aid}$	-179	74.82	5.66	-10.56	-378	-0.02	-0.09	0.07	0.54	-16.72^{**}	318
	(203)	(81.53)	(21.86)	(61.38)	(620)	(0.31)	(0.82)	(1.51)	(1.52)	(8.19)	(698)
N	171	262	205	300	48	437	251	309	251	194	422
Bandwidth	47.32	35.13	34.69	43.09	46.45	40.73	29.42	32.94	27.76	23.55	38.31
Wards	44	60	45	63	35	57	38	48	36	36	57

Running Variable: Distance to Single Point

	gorkha loss ever	high caste	age hh	highest ed	hhmembers	class5	class10	always lived house	always lived dist	NGO transfers	non quake aid
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$\widehat{Aid}$	$156,425^{*}$	-0.22	19.88	4.63	0.03	-0.51	-0.10	0.26	0.26	$14,609^{*}$	-135
	(94,240)	(0.38)	(12.33)	(2.98)	(1.06)	(0.36)	(0.41)	(0.22)	(0.22)	(8,506)	(3,686)
N	394	689	659	548	563	548	465	380	380	351	716
Bandwidth	43.73	62.9	61.13	55.29	55.89	54.76	49.05	42.57	42.57	42.16	63.91
Wards	59	91	85	77	77	82	71	57	57	60	91

	chicken price	rice price	lentil price	sugar price	mutton price	time to school	time to health	time to market	time to bank	slope	elevation
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$\widehat{Aid}$	-120	20.18	-32.60	12.49	-221	0.35^{**}	-0.05	-1.33^{**}	-1.23^{**}	-35.93^{**}	-947^{**}
	(96.17)	(14.66)	(25.54)	(20.07)	(230)	(0.15)	(0.26)	(0.59)	(0.56)	(14.63)	(389)
N	278	300	194	442	53	659	604	154	125	336	308
Bandwidth	69.27	46.12	41.73	61.32	51.79	61.16	57.52	30.16	28.68	41.05	40.7
Wards	76	61	53	84	39	88	78	31	28	57	54

TABLE B.VI

PLACEBO TESTS:

Local linear regressions with triangular kernel times survey weights, heteroskedasticity-robust standard errors. Slope of running variable allowed to differ on either side of cutoff. Using data from first survey wave before aid disbursements. Aid instrumented with Distance > 0. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels respectively.

	consumption	home investment	remittance income	cash savings	new loans taken	investments	total income	migration
Control for Damages:								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Aid}$	0.69*	10.48**	−14.95***	0.76	7.29	2.87	1.95*	−0.94**
	(0.40)	(4.53)	(5.71)	(3.13)	(4.65)	(3.22)	(1.06)	(0.44)
N	1259	1478	1572	1071	1440	1093	1223	1572
Bandwidth	37.54	43.78	45.64	34.76	42.62	34.48	37.14	45.22
Wards	66	66	66	64	66	66	66	66

	consumption	home investment	remittance income	cash savings	new loans taken	investments	total income	migration
Control for Damages, Demographics and Geography:								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Aid}$	0.71*	10.71**	−19.48**	−0.27	8.55	3.40	1.63	−1.21**
	(0.42)	(5.32)	(8.31)	(3.25)	(5.43)	(3.49)	(1.05)	(0.59)
N	1348	1350	1357	1334	1355	1355	1353	1442
Bandwidth	41.35	41.22	42.03	39.75	39.59	40.18	40.87	42.56
Wards	66	64	65	64	63	66	66	66

	consumption	home investment	remittance income	cash savings	new loans taken	investments	total income	migration
Dependent variable in Levels:								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Aid}$	111,707**	334,950*	−252,773**	53,928	35,153	146,875	578,033**	−0.76**
	(48,756)	(183,327)	(109,834)	(106,629)	(60,519)	(104,180)	(251,357)	(0.37)
N	777	955	917	898	1965	784	607	1093
Bandwidth	29.47	33.11	30.57	31.55	53.85	29.62	24.82	34.92
Wards	66	37	37	64	85	58	58	45

	consumption	home investment	remittance income	cash savings	new loans taken	investments	total income	migration
Dependent variable in Levels with Damage Controls:								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Aid}$	137,465**	343,105	−357,456**	69,048	81,507	185,569	959,000**	−0.94**
	(68,506)	(232,673)	(150,575)	(134,657)	(107,584)	(117,669)	(429,377)	(0.44)
N	953	1086	1572	940	1355	1223	783	1572
Bandwidth	32.57	35.01	46.08	32.58	40.62	37.15	28.29	45.22
Wards	66	37	66	64	66	71	66	66

	consumption	home investment	remittance income	cash savings	new loans taken	investments	total income	migration
Dependent variable in Levels with Damage/Demographic/Geography Controls:								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Aid}$	111,711*	285,866	−423,119**	−35,139	56,786	37,018	950,124**	−1.21**
	(63,854)	(205,770)	(185,634)	(91,612)	(92,394)	(75,117)	(453,441)	(0.59)
N	1303	778	1572	2450	1790	1965	1135	1442
Bandwidth	38.57	29.1	44.52	62.37	48.87	53.88	36.45	42.56
Wards	64	39	64	83	79	98	66	66

TABLE B.VII

ROBUSTNESS CHECKS

Local linear regressions with triangular kernel times survey weights, heteroskedasticity-robust standard errors. Slope of running variable allowed to differ on either side of cutoff. Full set of controls includes self-reported earthquake damages, age and education of the household head, a dummy for high caste, and the travel time to the nearest health clinic. Aid instrumented with Distance > 0. Except where otherwise indicated, all dependent variables in logs, with 1 added to home investment, remittances, cash savings, loans, investments, and migration to account for zeros. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels respectively.

Alternate Bandwidths:

	consumption	home investment	remittance income	cash savings	new loans taken	investments	total income	migration
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Aid}$	0.62**	2.03	−2.37	1.27	4.72*	1.44	1.00	−0.12
	(0.25)	(2.57)	(2.89)	(2.02)	(2.81)	(2.16)	(0.65)	(0.26)
N	472	473	476	460	475	476	476	476
Bandwidth	20	20	20	20	20	20	20	20
Wards	11	11	11	11	11	11	11	11

	consumption	home investment	remittance income	cash savings	new loans taken	investments	total income	migration
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Aid}$	0.68**	6.30**	−11.49**	0.60	5.47	2.07	1.86**	−0.66*
	(0.31)	(3.14)	(4.50)	(2.41)	(3.48)	(2.51)	(0.85)	(0.34)
N	864	866	872	853	871	872	870	872
Bandwidth	30	30	30	30	30	30	30	30
Wards	21	21	21	21	21	21	21	21

	consumption	home investment	remittance income	cash savings	new loans taken	investments	total income	migration
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Aid}$	0.58*	9.22**	−13.65***	0.69	6.51*	1.18	1.73**	−0.83**
	(0.31)	(3.68)	(5.18)	(2.55)	(3.76)	(2.57)	(0.86)	(0.39)
N	1348	1350	1357	1334	1355	1355	1353	1357
Bandwidth	40	40	40	40	40	40	40	40
Wards	32	32	32	32	32	32	32	32

	consumption	home investment	remittance income	cash savings	new loans taken	investments	total income	migration
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Aid}$	0.52**	9.55***	−10.51***	−0.36	5.48**	0.24	1.21**	−0.65**
	(0.23)	(2.85)	(3.50)	(1.92)	(2.74)	(1.95)	(0.61)	(0.27)
N	1827	1829	1836	1808	1834	1834	1832	1836
Bandwidth	50	50	50	50	50	50	50	50
Wards	44	44	44	44	44	44	44	44

	consumption	home investment	remittance income	cash savings	new loans taken	investments	total income	migration
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Aid}$	0.22	8.61***	−8.10***	−1.78	4.92**	−0.52	0.42	−0.46**
	(0.16)	(2.23)	(2.58)	(1.60)	(2.18)	(1.59)	(0.46)	(0.21)
N	2349	2353	2360	2323	2355	2357	2355	2360
Bandwidth	60	60	60	60	60	60	60	60
Wards	56	56	56	56	56	56	56	56

TABLE B.VIII

ROBUSTNESS CHECKS: ALTERNATE BANDWIDTHS

Local linear regressions with triangular kernel times survey weights, heteroskedasticity-robust standard errors. Slope of running variable allowed to differ on either side of cutoff. Aid instrumented with Distance > 0. All dependent variables in logs, with 1 added to home investment, remittances, cash savings, loans, investments, and migration to account for zeros. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels respectively.

	consumption	home investment	remittance income	cash savings	new loans taken	investments	total income	migration
Uniform Kernel:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Aid}$	0.42^{**}	4.44^{**}	-21.91^{**}	0.20	7.47	0.77	0.72	-0.65^{*}
	(0.19)	(2.09)	(9.17)	(1.62)	(4.70)	(1.69)	(0.49)	(0.35)
N	472	473	739	460	871	476	476	608
Bandwidth	22.56	20.2	26.22	22.81	30.09	18.46	19.36	24.01
Wards	32	36	39	32	50	27	27	32

	consumption	home investment	remittance income	cash savings	new loans taken	investments	total income	migration
Epanechnikov Kernel:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Aid}$	0.64^{**}	9.56^{**}	-2.53	0.24	6.81^{*}	1.91	0.98	-0.61^{*}
	(0.31)	(3.92)	(2.60)	(2.45)	(4.02)	(2.32)	(0.65)	(0.32)
N	777	1130	476	766	1355	739	435	739
Bandwidth	28.79	36.14	19.54	28.47	41.52	26.38	17.54	26.6
Wards	58	56	30	47	73	50	31	37

	consumption	home investment	remittance income	cash savings	new loans taken	investments	total income	migration
5 km Donut Hole:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Aid}$	0.04	3.43^{**}	-18.94^{***}	-3.51^{***}	1.39	-0.32	1.11	-0.69^{***}
	(0.23)	(1.37)	(6.91)	(0.89)	(1.39)	(1.24)	(0.81)	(0.21)
N	694	349	1228	335	391	392	1007	524
Bandwidth	28.04	17.06	38.33	16.82	22.7	20.59	35.68	24.67
Wards	60	28	57	29	30	29	85	35

	consumption	home investment	remittance income	cash savings	new loans taken	investments	total income	migration
Excluding Unaffected Districts:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Aid}$	0.68^{**}	9.74^{***}	-3.87	0.81	5.39	2.15	0.94	-0.65^{*}
	(0.32)	(3.63)	(2.80)	(2.15)	(3.43)	(2.56)	(0.61)	(0.34)
N	953	1478	608	721	783	917	476	828
Bandwidth	32.87	43.07	23.92	26.13	29.21	31.38	21.67	29.82
Wards	59	63	32	37	37	63	34	39

	consumption	home investment	remittance income	cash savings	new loans taken	investments	total income	migration
Inverse Hyperbolic Sine of Dependent Variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Aid}$	0.66^{**}	10.30^{***}	-6.82^{**}	0.92	6.03	1.26	0.93	-0.76^{**}
	(0.32)	(3.99)	(3.39)	(2.70)	(3.78)	(2.74)	(0.61)	(0.37)
N	1084	1435	695	984	916	1310	476	1093
Bandwidth	33.92	42.3	25.32	33.48	31.29	38.93	22.07	34.92
Wards	66	66	35	47	40	77	35	45

TABLE B.IX

ROBUSTNESS CHECKS: ALTERNATE KERNELS AND OTHER

Local linear regressions with triangular kernel times survey weights, heteroskedasticity-robust standard errors. Slope of running variable allowed to differ on either side of cutoff. Aid instrumented with Distance > 0. Donut hole drops villages within 5km of either side of the border. Except where otherwise indicated, all dependent variables in logs, with 1 added to home investment, remittances, cash savings, loans, investments, and migration to account for zeros. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels respectively.

Distance to Single Point with Control Variables:

	consumption	home investment	remittance income	cash savings	new loans taken	investments	total income	migration
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Aid}$	0.08	3.97*	−4.37	−0.86	4.78*	0.06	0.32	−0.35
	(0.23)	(2.38)	(2.71)	(2.02)	(2.53)	(1.98)	(0.54)	(0.23)
N	952	2394	2143	1593	2183	1792	2396	2401
Bandwidth	40.63	67.38	62.67	51.19	63.14	56.3	67.83	67.71
Wards	54	98	85	69	87	75	99	98

Distance to Single Point with Dependent Variable in Levels:

	consumption	home investment	remittance income	cash savings	new loans taken	investments	total income	migration
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Aid}$	54,149*	247,366**	−86,271	14,457	15,552	−99,357	322,388**	−0.38
	(29,105)	(105,611)	(61,909)	(64,056)	(54,237)	(110,729)	(159,599)	(0.26)
N	344	1831	1705	1636	2311	2794	1043	1224
Bandwidth	27.52	57.1	54.92	51.77	66.18	80.23	41.97	42.74
Wards	32	78	85	84	80	85	66	57

Using Border of All 14 Districts:

	consumption	home investment	remittance income	cash savings	new loans taken	investments	total income	migration
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Aid}$	−0.03	1.04	−3.29	−5.27**	−0.39	−4.91***	0.67	−0.19
	(0.18)	(1.78)	(2.44)	(2.20)	(1.83)	(1.83)	(0.61)	(0.19)
N	2104	2194	2679	2873	2021	2153	2329	2108
Bandwidth	14.79	17.1	19.61	23.25	13.95	15.16	17.7	14.46
Wards	89	102	103	148	95	102	100	78

Using Border of All 14 Districts with Control Variables:

	consumption	home investment	remittance income	cash savings	new loans taken	investments	total income	migration
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{Aid}$	0.11	0.97	−1.62	1.12	−2.28	−5.24**	1.86**	−0.41*
	(0.21)	(2.01)	(2.71)	(2.03)	(2.48)	(2.23)	(0.87)	(0.25)
N	1665	1975	2197	2176	2196	1801	2329	1669
Bandwidth	11.33	13.21	16.02	16.56	16.12	12.51	17.64	11.79
Wards	70	93	102	103	107	96	107	74

TABLE B.X

ROBUSTNESS CHECKS: ALTERNATE RUNNING VARIABLE DEFINITIONS

Local linear regressions with triangular kernel times survey weights, heteroskedasticity-robust standard errors. Slope of running variable allowed to differ on either side of cutoff. Full set of controls includes self-reported earthquake damages, age and education of the household head, a dummy for high caste, and the travel time to the nearest health clinic. Aid instrumented with Distance > 0. Single point is the point on the Western border of the 14 most-affected districts that is closest to any village. Except where otherwise indicated, all dependent variables in logs, with 1 added to home investment, remittances, cash savings, loans, investments, and migration to account for zeros. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels respectively.

APPENDIX C: APPENDIX C. DETERMINANTS OF EARTHQUAKE DAMAGES AND EFFECT OF EARTHQUAKE ON INCOME

A. All Survey Waves

	log(income)				
	(1)	(2)	(3)	(4)	(5)
(Intercept)	11.752***	11.522***	11.717***	11.456***	14.876***
	(0.009)	(0.053)	(0.012)	(0.381)	(1.286)
Earthquake Losses (000s NPR)	0.000	0.000	0.001***	0.020***	0.020***
	(0.000)	(0.000)	(0.000)	(0.008)	(0.007)
log(elevation)					−0.310***
					(0.110)
log(distance to epicenter)					−0.229
					(0.148)
Observations	16 742	16 742	16 742	16 742	16 742
R2	0.000	0.043	−0.013	−4.636	−4.581
Fixed Effects		Village + Wave		District + Wave	District + Wave
IV			Shake Intensity	Shake Intensity	Shake Intensity

B. First Survey Wave

	log(income)				
	(1)	(2)	(3)	(4)	(5)
(Intercept)	11.587***	11.566***	11.574***	11.770***	15.160***
	(0.015)	(0.085)	(0.019)	(0.498)	(1.524)
Earthquake Losses (000s NPR)	0.000	0.000	0.000	0.015	0.014*
	(0.000)	(0.000)	(0.000)	(0.009)	(0.007)
log(elevation)					−0.268**
					(0.124)
log(distance to epicenter)					−0.237
					(0.181)
Observations	5547	5547	5547	5547	5547
R2	0.000	0.032	−0.002	−3.105	−2.361
Fixed Effects		Village		District	District
IV			Shake Intensity	Shake Intensity	Shake Intensity

TABLE C.I

EFFECTS OF EARTHQUAKE DAMAGES ON INCOME.

Panel A tests the effect of earthquake losses on log income using all three survey waves. Since households that experienced earthquake losses also were more likely to receive aid, this could include the effects of aid. Panel B tests the effect of earthquake losses on log income in the first survey wave before reconstruction aid disbursements began and finds fairly precise null effects, although the final two columns are positive and borderline significant. If anything this would bias estimates of WTP higher for households with higher earthquake damages. In both panels, column 1 is estimated using OLS. Column 2 adds village dummies and survey wave fixed effects in Panel A. Since higher losses could be associated with bigger houses and wealthier households, columns 3-5 instrument for earthquake losses using earthquake intensity (peak ground acceleration from USGS). Columns 4 and 5 add district dummies to control for regional differences in incomes, as well as wave fixed effects in panel A. Column 5 adds additional controls for elevation and distance to the epicenter. Earthquake losses self reported in thousands of NPR. Households with zero or missing income or less than 3 observations dropped. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	Aid Eligible			
	(1)	(2)	(3)	(4)
Foundation:Cement/Stone/Brick	−0.084***			
	(0.003)			
Foundation:Mud mortar-Stone/Brick	0.162***			
	(0.002)			
Foundation:Other	0.041***			
	(0.007)			
Reinforced Concrete	−0.412***			
	(0.003)			
Roof:Bamboo/Timber-Light		0.018***		
		(0.001)		
Roof:Reinforced Concrete		−0.477***		
		(0.002)		
Total Square Feet			−0.0001***	
			(0.00000)	
Death or Injury occurred				0.056***
				(0.003)
N	747,137	747,137	747,137	747,137
R^2	0.355	0.346	0.305	0.299

TABLE C.II

BUILDING MATERIALS

Estimated from post earthquake building census in the 11 most affected districts. Dependent variable is whether households were deemed eligible for aid, which indicates that engineers scored the damage to their home as a 4 or 5 on a 1-5 scale. Excluded category in column 1 is Bamboo/Timber foundation. Excluded category in column 2 is Heavy Bamboo/Timber roof. All regressions include village dummies. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels respectively.

	Aid Eligible				
	(1)	(2)	(3)	(4)	(5)
Owned TV	−0.064***				
	(0.001)				
Owned Mobile Phone		−0.040***			
		(0.001)			
Owned Land			0.074***		
			(0.002)		
Income: Rs. 10-20k NPR				−0.047***	
				(0.001)	
Income: Rs. 20-30k NPR				−0.085***	
				(0.002)	
Income: Rs. 30-50k NPR				−0.102***	
				(0.003)	
Income: Rs. 50k+ NPR				−0.118***	
				(0.005)	
Has Bank Account					−0.052***
					(0.001)
N	747,137	747,137	747,137	747,137	747,137
R^2	0.302	0.300	0.300	0.303	0.301

TABLE C.III

HOUSEHOLD ASSETS AND INCOME

Estimated from post earthquake building census in the 11 most affected districts. Dependent variable is whether households were deemed eligible for aid, which indicates that engineers scored the damage to their home as a 4 or 5 on a 1-5 scale. All regressions include village dummies. Excluded category in column 4 is income under 10 thousand. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels respectively.

	Aid Eligible				
	(1)	(2)	(3)	(4)	(5)
Migrant Connected	−0.002**				
	(0.001)				
Receives Social Security		0.026***			
		(0.001)			
Male Headed Household			0.036***		
			(0.001)		
Finished High School				−0.059***	
				(0.002)	
Some Middle/High School				−0.027***	
				(0.001)	
Newar					−0.054***
					(0.002)
Other Caste					0.006***
					(0.001)
N	747,137	747,137	747,137	747,137	747,137
R^2	0.299	0.299	0.300	0.300	0.300

TABLE C.IV

HOUSEHOLD DEMOGRAPHICS

Estimated from post earthquake building census in the 11 most affected districts. Dependent variable is whether households were deemed eligible for aid, which indicates that engineers scored the damage to their home as a 4 or 5 on a 1-5 scale. Excluded category in column 4 is less than high school. Excluded category in column 5 is high caste (Brahmin/Chhetri). All regressions include village dummies. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels respectively.

APPENDIX D: APPENDIX D. ALTERNATE COUNTERFACTUALS

	Targeting Scenario						
	Actual	Damages	Shake Intensity	Consumption	Liquidity	Universal	Optimal
Welfare Measure	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				$\gamma = 1.2$ *and* $\beta = .926$			
WTP	1.06	1.07	1.09	0.98	0.91	1.02	1.50
	(1.02, 1.08)	(1.03, 1.09)	(1.05, 1.11)	(0.95, 1.01)	(0.86, 0.94)	(1.00, 1.03)	(1.45, 1.52)
Utilitarian	0.98	0.97	0.98	1.05	0.99	0.98	1.75
	(0.94, 1.02)	(0.92, 1.01)	(0.94, 1.01)	(1.00, 1.08)	(0.93, 1.03)	(0.96, 1.00)	(1.72, 1.82)
				$\bar{h} = 0.095$			
WTP	1.09	1.10	1.10	1.01	1.09	1.07	1.57
	(1.04, 1.12)	(1.05, 1.12)	(1.06, 1.12)	(0.97, 1.03)	(1.05, 1.13)	(1.05, 1.09)	(1.51, 1.59)
Utilitarian	0.45	0.51	0.31	1.32	2.28	1.05	2.62
	(0.16, 0.64)	(0.18, 0.71)	(0.10, 0.44)	(0.75, 1.80)	(2.11, 2.49)	(0.68, 1.43)	(2.53, 2.80)
				P_{it} *based on pre-quake*			
WTP	1.09	1.10	1.10	0.99	1.00	1.04	1.52
	(1.05, 1.11)	(1.06, 1.13)	(1.06, 1.12)	(0.95, 1.02)	(0.96, 1.03)	(1.02, 1.06)	(1.46, 1.54)
				P_{it} *based on post-aid*			
WTP	1.05	1.06	1.08	0.99	1.00	1.04	1.52
	(1.02, 1.08)	(1.03, 1.09)	(1.04, 1.10)	(0.95, 1.02)	(0.96, 1.03)	(1.02, 1.06)	(1.46, 1.53)

TABLE D.I

COUNTERFACTUAL TARGETING SCENARIOS

Benefits relative to a random allocation for 300,000 NPR aid allocated to 38% of the population according to various targeting strategies – except universal scenario which uses 0.38*300,000 NPR allocated to the entire population. Bootstrapped 95% confidence intervals in parentheses using survey weights. Utilitarian refers to an ‘equal-weighted’ utilitarian social welfare function. Consumption and liquidity allocations based on households with the lowest values of those variables. Damages based on households with the highest self-reported earthquake damages. Shake Intensity based on villages with the highest peak-ground acceleration from USGS.

	w = 0.5	w = 1	w = 2
$g = 1$	-7.3%	1.6%	3.6%
$g = 2$	-3.8%	0.5%	7.0%

TABLE D.II

ALTERNATE STATE VARIABLE DISTRIBUTIONS:
Aggregate Welfare Improvement from Targeting Relative Universal Allocation