Policy Research Working Paper 10668

# Costing Disasters

## Hedonic Pricing, Neighborhood Effects, and the Nepal Gorkha Earthquakes

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WORLD BANK GROUP
South Asia Region
Office of the Chief Economist
January 2024

## Abstract

Disasters are frequent and clearly harmful in developing countries, but precisely estimating their overall cost and distributional impact is challenging. This paper proposes a microsimulation approach to do so rapidly, borrowing concepts from both poverty analysis and urban economics. Because housing prices reflect the present value of a specific bundle of living conditions, local earnings opportunities, and local access to services, their change in the aftermath of a disaster can be interpreted as a measure of the welfare cost incurred by households. A hedonic pricing function is used to estimate such changes based on the destruction experienced by the dwellings themselves, but also on the overall destruction suffered by their surrounding areas. The first element captures the damage from worse living conditions, whereas the second captures the loss from diminished earnings opportunities and access to services. The proposed approach is illustrated by estimating the cost of the 2015 Gorkha earthquakes in Nepal. Overall, the estimated impact is comparable to that from the official assessment. But its spatial distribution is significantly different due to the pivotal influence of neighborhood effects.


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# Costing Disasters: Hedonic Pricing, Neighborhood Effects, and the Nepal Gorkha Earthquakes

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**Keywords:** Earthquakes, Hedonic Prices, Imputed Rent, Housing, Microsimulation, Natural Disasters, Neighborhood Effects, Nepal, Spatial Economics, Welfare.

**JEL:** C31, D60, I30, O18, Q54, R12, R20, R21, R23

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* Vincent A. Floreani is with the European Investment Fund and Martin Rama with the World Bank. The corresponding author is Vincent Floreani at v.floreani@eif.org. The authors gratefully acknowledge insightful comments and suggestions by Virgilio Galdo, Hemang Karelia, Yue Li, Sailesh Tiwari, Hiroki Uematsu, and participants at the 21st Journées Louis-André Gérard-Varet held in Marseille on June 7, 2022. The findings, interpretations, and conclusions in the paper are entirely those of the authors. They do not necessarily represent the views of the organizations the authors are affiliated with.

## 1. Introduction

Natural disasters are frequent and hugely costly in terms of human life and household welfare. Just in 2015, the year of the massive Gorkha earthquakes in Nepal, 396 disasters were recorded worldwide with poorer nations accounting for 95 of the 119 countries affected (EM-DAT database, accessed in May 2016). Historically, developing countries have experienced 80 percent of the disasters recorded (Noy 2009). With a greater share of their population living in poverty, and with more limited fiscal space to cope, poorer nations are bound to experience greater hardship (Fomby, Ikeda & Loayza 2013). How much greater, however, is difficult to tell (Kliesen and Stuart Mill 1994).

The most obvious cost of a disaster stems from the human deaths and injuries it causes. Estimating this cost requires some measure of the statistical value of life, an issue with its own methodological challenges that this paper does not attempt to address.

Beyond these direct human impacts, disasters often result in a major fall in household welfare. Part of the fall stems from the destruction of dwellings caused by the disaster, and part of it is from its indirect consequences on economic activity and access to services. Sometimes these two components are called *damage* and *loss*, respectively. Boundaries between them are not always easy to delineate. Intuitively, however, mangled assets fall in the first category, whereas business disruptions belong in the second one (Hallegatte and Przyluski 2010).

The actual cost of a disaster could in principle be assessed through private insurance claims and government-provided emergency support, with the former yielding an estimate of damages and the latter of losses. However, formal insurance coverage is partial in developing countries, and government support in the aftermath of a disaster is most often insufficient. This kind of assessment would therefore result in gross underestimates. In the absence of direct information of the sort available in advanced economies, estimates of the cost of natural disasters in developing countries need to be based on other data sources, combined with defensible assumptions.

This paper proposes a rigorous approach to rapidly assess the cost of natural disasters and its distribution across localities and population groups, using a relatively limited information set. The proposed approach combines concepts borrowed from poverty measurement and urban economics. Its two key tenets are to focus on the value of dwellings and to explicitly model how this value is affected by disasters, both directly and indirectly.

Poverty analyses have shown that dwellings are not only an essential part of households' wealth: they are also an important component of their utility and propensity to consume (Lipton and Ravallion 1995, Berger et al. 2018, and Ceriani et al. 2023). Housing constitutes a good proxy for households' welfare and its distribution across households provides a credible measure of inequality in developing countries (Van der Weide et al. 2018). In the approach proposed by this paper, the value of dwellings is captured through *imputed housing prices* – how much households think their homes are worth.

Urban economics, in turn, has shown that housing prices are very much linked to local economic conditions. At the aggregate level, housing prices are positively correlated with economic activity (Aizenman et al. 2016). But at the local level they are influenced by *neighborhood effects,* or local spillovers whose impact decreases with distance (Goodman 1978, Durlauf 2004, Rossi-Hansberg et al. 2010, Ioannides 2010). The choice of a dwelling to shelter in and a neighborhood to live in are indeed joint decisions, influenced by the characteristics of the dwelling, but also by the social interactions, earnings opportunities and public services the neighborhood gives access to.

Because housing is a good proxy for household welfare, and housing prices are affected by local conditions, the change in the value of dwellings in the immediate aftermath of a disaster can be interpreted as a measure of the welfare loss experienced by their occupants. This interpretation does not require assuming that housing is the only household asset, but only that other assets and liabilities they may hold – such as cash or informal debt – are not affected by the disaster, and especially by its impact on their neighborhoods.

The change in imputed housing prices is estimated through *hedonic pricing functions*. These are regressions that include among their explanatory variables the characteristics of the dwelling and those of the location it sits in (Balcazar et al. 2017, Silver 2016). The proposed approach pays special attention to neighborhood effects. In the same way as more prosperous neighborhoods are more attractive, eliciting a greater local demand for housing, more severely damaged neighborhoods should experience a greater decline – in relative terms – in the value of their dwellings. The estimation builds on the theoretical underpinnings provided by Grieson and White (1989) and is informed by applications to the United States by Ioannides and Zabel (2003) and to China by Song and Zenou (2012).

The estimated change in imputed housing prices in the aftermath of a disaster can in turn be decomposed into two elements. First is the fall in the value of a dwelling resulting from the physical destruction it suffered; this first element reflects the change in the present value of living conditions and can be linked with the damage concept. Second is the fall stemming from the destruction experienced by the surrounding area; this second element indicates the change in the present value of earnings opportunities and access to services associated with the dwelling, similar in spirit to the loss concept.

The only two requirements to implement the proposed approach are the availability of disaggregated information on imputed housing prices and dwelling characteristics before the disaster, and of geographically disaggregated information on the condition of physical assets in its aftermath. In practice, data on housing prices and characteristics can often be obtained from a representative household survey, and data on the extent of destruction of assets from either a field survey or satellite images.

The first step toward implementing the proposed approach is to use household survey data to estimate a hedonic price function for the value of dwellings before the disaster, with the specification including a neighborhood effect. Second, plausible rules are used to allocate the local destruction rates of physical assets of different types to individual households in the survey. Third, in the spirit of microsimulations, these rules allow predicting new imputed housing prices for the damaged dwellings. Fourth, the predicted average value of all dwellings in each geographic area is computed. And fifth, plugging these new neighborhood effects in the hedonic price function allows predicting new imputed housing prices for all dwellings. Steps four and five are then repeated until imputed housing prices converge to stable values.

The proposed approach is illustrated in the case of Nepal, a country with a high vulnerability to natural disasters (World Bank 2022). The focus is on the cost of the 2015 Gorkha earthquakes. At the aggregate level, this exercise yields a disaster cost similar in magnitude to the one jointly reported by the Post-Disaster Needs Assessment (PDNA) conducted in the months that followed (National Planning Commission 2015). At a more disaggregated level, however, the estimated disaster cost is significantly higher in the most severely affected districts, and lower elsewhere. The main reason for the discrepancy with the official assessment stems from the strength of neighborhood effects in the worst-hit localities.

## 2. Relationship to the literature

The focus on the value of dwellings marks a departure from previous approaches to assess the cost of disasters, which have tended to rely on other *indicators*. Simplifying, those other indicators include national accounts, field surveys of physical assets, and satellite images.

Before-and-after comparisons of national accounts data on aggregate output and its components provide a straightforward way to assess the impact of disasters in developing countries. Given the large number of events occurring worldwide in every single year, the number of observations available to conduct comparisons of this sort is substantial. Large samples, in turn, allow to qualify impacts depending on the type of disaster, its magnitude and the country’s development level (Loayza et al. 2012). Some studies have even focused on narrower sets of disasters, such as storms (Ishizawa and Miranda 2019), hurricanes (Strobl 2012), and earthquakes (Webb et al. 2002).

Studies based on this approach have shown that severe disasters trigger significant contractions in output and trade (Gassebner et al. 2010). However, their estimates are quite sensitive to assumptions, especially because observed income in the years following a disaster may be boosted by reconstruction-related investments. Moreover, with few exceptions (Kashiwagi et al. 2021), estimates based on national accounts fail to provide a breakout of the cost by geographic areas, which is critically important to target support. Importantly, waiting for the release of reliable national account data may not be practical when quick estimates are needed to guide assistance and reconstruction efforts on the ground.

Rapid field surveys like those conducted in the context of PDNAs address some of these concerns. Field surveys typically focus on the geographic areas most affected by disasters. Teams on the ground take stock of existing public and private assets, assess their condition in the aftermath of the disaster, and collect qualitative input from local economic agents. The result is a rich information set that is used to forecast the impact of the disaster on local economic activity and access to services, to estimate the cost of asset reconstruction or replacement, to identify the most urgent needs, and on that basis to establish a recovery strategy.

This second approach tends to be comprehensive and has produced useful estimates of the cost of disasters, often in a matter of just weeks or months. However, one of the main challenges it faces is to convert the information on physical destruction into monetary values. A baseline reporting of the market value or investment cost of public and private assets prior to the disaster is generally unavailable and educated guesses on the spot may carry a significant margin of error. Assessing in monetary terms the change in earnings opportunities and in access to services can be even more challenging. Because of these difficulties, the precision and relevance of studies based on this second approach has been questioned (Jeggle and Boggero 2018).

An alternative to using field survey data is relying on remote-sensing technology. Proceeding this way allows for greater measurement consistency across geographic areas and provides real-time estimates. Studies based on this third approach have leveraged satellite images on built-up areas and nighttime light intensity to infer the impact of natural disasters at local levels. For example, an analysis of Chinese typhoons shows that when 50 percent of properties in an area are destroyed, local economic activity falls by 20 percent (Elliott et al. 2015).

The advantages of this third approach include the speed at which cost estimates can be generated, and their high spatial granularity. However, there are disadvantages as well. Built-up data allows assessing the extent of physical destruction, less so the market value of the assets destroyed. Similarly, nighttime light intensity provides information on long-term trends in economic activity, especially across countries and regions, but is less well-suited to assess its short-term fluctuations (Ezran et al. 2023). And satellite images may not be sufficient to disentangle the impact of disasters across population groups.

On the other hand, the approach proposed in this paper is closely linked to the existing literature on disasters through its reliance on *microsimulations*. These are computational exercises that use disaggregated data on assets and earnings from previous household surveys or population and housing censuses to assess how each household in the sample may be affected by specific disasters.

In this spirit, Rozenberg and Hallegate (2016) harmonized representative household surveys for 89 emerging and developing countries, and estimated that "altogether earthquakes, storm surges, tsunamis and cyclones bring between 300,000 and 2.9 million people into extreme poverty on average per year". Similarly, Skoufias et al. (2020) developed a microsimulation model for the Philippines to estimate household vulnerability to natural disasters of different types and intensities.

An important strength of microsimulations is their ability to generate impact estimates by population groups and geographic areas. However, an analytical framework aggregating the various impacts into a welfare loss is often missing. For example, a given fraction of assets of different types and of labor earnings in different sectors may be deemed lost. But the impact on specific households is bound to vary with their endowments and occupations prior to the disaster.

## 3. The proposed approach

Consider a country that consists of multiple geographical areas, such as districts, towns and villages, with $h$ economic agents – households, firms and local governments – living and working in geographic area $i$. Each of these areas is characterized by a stream of monetary incomes from local economic opportunities and of non-monetary services from local amenities.

Let $Y^h$ be the monetary value of opportunities and amenities enjoyed by agent $h$ during a given period – say, a year. The simplest approach to the cost $C^h$ experienced by agent $h$ in the wake of a disaster is:

$$C^h = \left(Y_0^h - Y_1^h\right)/r \tag{1}$$

where 0 is the period preceding the disaster, 1 the following period, and $r$ the discount rate. Equation (1) indicates the present value of the foregone opportunities and amenities due to the disaster.

The cost for the entire geographic area $i$ can be obtained by aggregating the cost experienced by all the households living and working in it:

$$C^i = \left(Y_0^i - Y_1^i\right)/r \qquad \text{with} \qquad Y^i = \sum_i Y^h \tag{2}$$

Another way to express the cost experienced by agent $h$ is in relation to the stock and value of its assets before and after the disaster. Let $K^h$ be the assets of agent $h$ and $p^i$ be the price of a unit of capital in area $i$. Given the local externalities considered by urban economics, this price can vary geographically, with its dispersion potentially amplified by barriers to capital mobility across geographical areas. The cost is then:

$$C^h = K_0^h . p_0^i - K_1^h p_1^i \tag{3}$$

Note that agent $h$ can experience a welfare loss even if its assets emerge unscathed from the disaster ($K_0^h = K_1^h$). This is because opportunities and amenities are bound to fall by a greater extent in areas more severely affected by the disaster, and this in turn should affect to a greater extent the local return to capital. Intuitively, even dwellings that were not directly damaged can be expected to lose value if the surroundings have been turned into rubble.

Once again, this expression can be aggregated over an entire geographic area, which yields:

$$C^i = K_0^i . p_0^i - K_1^i p_1^i \qquad \text{with} \qquad K^i = \sum_i K^h \tag{4}$$

The local value of capital can be expected to reflect the discounted value of opportunities and amenities that can be enjoyed by living and working in the area:

$$p^i = \frac{Y^i}{rK^i} \qquad \text{With} \qquad K^i = \sum_i K^h \tag{5}$$

If so, equations (2) into (4) are equivalent, and any of them can be used to measure the cost of disasters. However, an advantage of relying on equation (4) is that it can be easily decomposed into the standard loss and damage components. Indeed, adding and subtracting $K_1^i p_0^i$ allows rewriting equation (4) as:

$$C^h = \left(K_0^h - K_1^h\right) p_0^i + K_1^h \left(p_0^i - p_1^i\right) \tag{6}$$

The first term in the right-hand-side of equation (6) captures the original value of the assets destroyed by the disaster (or damage), the second one the reduction in value of the surviving assets (or loss).

The proposed approach attempts to quantify equation (6) by predicting the change in the local price of assets based on the information available on the extent of their physical destruction. To do so, it uses data on the market value of dwellings $V^h$, defined as:

$$V^h = K^h p^i \tag{7}$$

In developing countries property titles are not always formalized, real estate transactions are partially documented at best, and many households occupy their dwellings without paying rent, so $V^h$ may not be directly observable. However, the household surveys used for poverty measurement generally ask respondents how much they would have to pay for the place they live in if they had to rent it. This value often provides a good proxy for housing prices in developing countries.

The market value of a dwelling can be expected to increase with its quality. Characteristics such as its overall surface, the materials used for its construction, or its access to water and sanitation should, other things equal, have an impact on its price. But the same dwelling should also be worth more in a "good" neighborhood. Areas with better schools, easier access to markets or lower crime rates should indeed carry a premium. And the average market value of dwellings in the area is another important indicator to assess how "good" a neighborhood is.

The relationship between the market value of dwellings on the one hand and their specific characteristics and those of their localities on the other is known as a hedonic price function. In the proposed approach, this function is specified as:

$$V^h = f(X^h, L^i, V^i) + \varepsilon^{hi} \qquad \text{with} \qquad V^i = \sum V^h / H^i \tag{8}$$

where $X^i$ captures the physical characteristics of each dwelling, $L^i$ those of the locality it sits in, and $V^i$ the average value of dwellings in the areas. The last term, $\varepsilon^{hi}$, is a stochastic disturbance with zero mean that is independently distributed across households but whose variance may be different across locations.

The approach proposed in this paper to assess the cost of disasters is to use recent microeconomic data on $V^h$, $X^h$ and $L^i$ to estimate equation (8). Then, data from a field survey or satellite imagery are used to assess how the characteristics $X^h$ of each individual dwelling might have been affected. With this assessment at hand, it is possible to use the estimated equation (8) to predict the post-disaster values of $V^h$ and, by extension, of $V^i$. This information then allows computing the decomposition in equation (6) for all areas affected by the disaster.

## 4. The Gorkha earthquakes

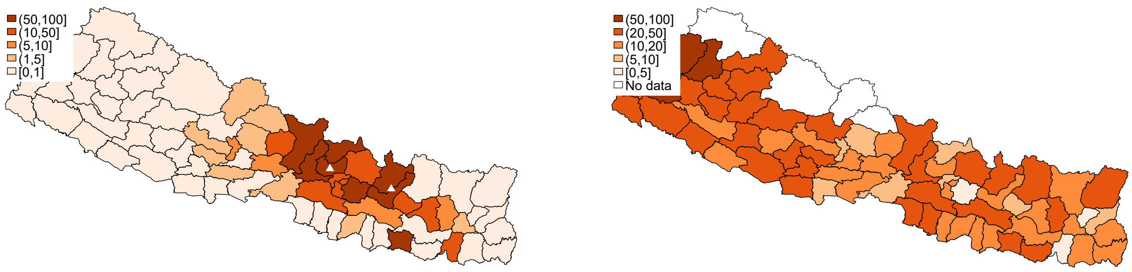
Triggered by a slip in the Main Frontal Thrust, the Gorkha earthquakes were Nepal's worst natural disaster since 1934. The first wave struck on the 25th of April 2015, with a Richter magnitude of 7.5. Its epicenter was in Barpak, in Gorkha District. It was followed by a major aftershock on the 12th of May 2015, with a 7.4 magnitude. Its epicenter was at the border of the Dolakha and Sindhupalchowk districts. These high-intensity quakes triggered a large human toll: 8,961 deaths and 22,302 injuries (Government of Nepal 2015).

The epicenter of the first Gorkha earthquake is located 80km away from the capital city of Kathmandu, and that of the aftershocks is 60km away. The affected area encompasses the Western, Central and Eastern Hills (figure 1.a). These regions are relatively well-off by Nepalese standards (figure 1.b). However, Nepalese households display a high degree of vulnerability even under normal circumstances (Tiwari et al. 2016). Besides, the districts affected are populous, with housing of poor quality, so that very significant impacts could be expected.

A PDNA was conducted by the Government of Nepal, in collaboration with international partners, in the immediate aftermath of the disaster. The assessment covered 31 districts affected by the earthquakes and aimed to assess impacts across sectors of activity and social groups. Field visits were conducted to evaluate the destruction of housing, infrastructure and social amenities, and to estimate the impact on production of goods and delivery of services. Specific sector teams assessed damages, losses and recovery needs in the 14 worst-affected districts.

**Figure 1. The Gorkha Earthquakes hit areas that were not among the poorest in Nepal**

*a. Dwellings destroyed (percent of the total)* *b. Poverty rate (percent of the population)*




*Note:* The triangles in panel a represent the earthquakes' epicenters.

*Source:* Central Bureau of Statistics of Nepal (2012b) and Government of Nepal (2015) for panel a and Central Bureau of Statistics of Nepal (2012a) for panel b.

Reportedly, 776,895 private houses – 12 percent of the total housing stock recorded by the 2011 population census – had been destroyed (Government of Nepal 2015). Given that before the earthquakes imputed rent for housing accounted for about 12 percent of overall household consumption expenditure, the likely impact on household wellbeing was massive. The PDNA evaluated the average loss per capita at USD 171, large enough to have pushed between 700,000 and 980,000 additional people into poverty (Tiwari and Uematsu 2015). Not surprisingly, the destruction of dwellings accounted for 25 percent of the total estimated losses from the Gorkha earthquakes, and for 60 percent of the total damages (National Planning Commission 2015).

## 5. Data description

The dataset used to illustrate the proposed approach to estimating the cost of disasters combines information from three sources. These are: a household survey conducted in 2010/11 (Central Bureau of Statistics of Nepal 2012a), from the 2011 population and housing census (Central Bureau of Statistics of Nepal 2012b), and from official figures on assets/housing destructions covered by the Disaster Recovery and Reconstruction Information Platform established following the Gorkha earthquakes (Government of Nepal 2015).

The first of these three sources, the Nepal Living Standards Survey III (NLSS III), reports data on multiple welfare dimensions for 5,998 households in 2010/11. Its sampling frame is representative at the level of districts or Village Development Committees (VDCs).

Households are not geocoded in the NLSS III dataset but the districts or VDCs they live in are. The latter are taken as the reference geographic areas in what follows. It should be noted that in September 2015, as Nepal embraced a federalist government structure, its more than 3,100 districts and VDCs were consolidated under 753 local governments in seven provinces. However, this regrouping does not affect the analysis.

In addition to welfare-related indicators, the NLSS III contains household-level data on dwelling configuration, occupancy, endowments, and location. Imputed housing prices come from selfassessments, consistent with the approach proposed by Ceriani et al. (2019). There is also information on physical housing characteristics, including type of construction, floors, water and electricity connections, sanitation and the like.

Information on district characteristics is taken from the 2011 population census, which was conducted roughly at the same time as the NLSS III. The resulting housing stock measure is combined with official figures to estimate the proportion of dwellings destroyed in each district (Government of Nepal 2015).

A detailed description of the variables used in the regression analysis can be found in the annex (table A.1). Their summary statistics are reported there as well (table A.2). Among other insights, these summary statistics show that self-assessed housing rents before the Gorkha earthquakes were higher in the most affected districts (the ones where at least 5 percent of the dwellings have been fully destroyed) than in the rest of the country.

## 6. The hedonic pricing regression

The hedonic price function in equation (8) is estimated with self-assessed rent as the dependent variable. The alternative would be to use self-assessed housing price, but there are much fewer observations available for this variable. Given the characteristics of the data and the conceptual options available, four specifications are considered (table 1). A first choice is whether to define neighborhood effects at the district level (first two columns) or at the narrower VDC level (last two). A second choice is whether to assume that the impact of neighborhood effects is linear (columns one and three) or quadratic (columns two and four).

The overall significance of the model is strong in all cases. Adjusted $R^2$ statistics are in the range of 0.58-0.64, highlighting the good fit of the model. The reliability of the estimates is further confirmed by the F-statistics, which are statistically significant at the 5-percent level for all specifications and at the 1-percent level for most of them. As for individual determinants, almost all coefficients on dwelling characteristics and local amenities are statistically significant at the 10-percent level. Most of them are even significant at the 1-percent level.

Reassuringly, the signs and magnitudes of the coefficients are similar across specifications. In all cases, the main determinants of imputed housing prices are the dwelling's type of foundation and roof, the public services it has access to, and location characteristics. Occupancy indicators, including whether the household rents the dwelling or owns it, and whether it shares it with other households or not, also appear to be strong predictors of self-assessed housing rents.

The coefficients obtained for neighborhood effects are always significant at the 10-percent level and reach the 1-percent level in most cases. The magnitude of the coefficients is larger when neighborhood effects are computed at the VDC level, rather than at the district level. This result is consistent with a decrease of local spillovers with distance. The specifications using a quadratic form reveal that local spillover effects are concave, mattering less in relatively wealthier communities than in poorer areas.

## Table 1. The hedonic pricing regression for self-assessed rent

| | Neighborhood effect level | District | District | VDC | VDC |
|---|---|---|---|---|---|
| | Neighborhood effect model | Linear | Quadratic | Linear | Quadratic |
| Dwelling | Land plot (log Ha) | 0.051 *** | 0.012 | 0.057 *** | 0.055 *** |
| | Dwelling area (log sq ft) | 0.214 *** | 0.233 *** | 0.238 *** | 0.238 *** |
| | Number of rooms | 0.128 *** | 0.129 *** | 0.114 *** | 0.114 *** |
| | Dwelling has a kitchen | 0.181 *** | 0.156 *** | 0.161 *** | 0.159 *** |
| | Dwelling has a cement wall | 0.189 *** | 0.207 *** | 0.156 *** | 0.160 *** |
| | Dwelling has pillar or cement foundation | 0.245 *** | 0.279 *** | 0.224 *** | 0.228 *** |
| | Dwelling has tin or cement roof | 0.339 *** | 0.250 *** | 0.280 *** | 0.278 *** |
| | Dwelling has windows | 0.254 *** | 0.244 *** | 0.211 *** | 0.219 *** |
| | Dwelling has piped water supply | 0.030 | -0.007 | 0.031 | 0.035 |
| | Dwelling has piped water | 0.190 *** | 0.196 *** | 0.131 *** | 0.132 *** |
| | Paved road next to dwelling | 0.312 *** | 0.336 *** | 0.120 *** | 0.140 *** |
| | Year dwelling was built | 0.001 | 0.001 * | 0.001 | 0.001 |
| | Dwelling is rented | -0.221 *** | -0.222 *** | -0.306 *** | -0.298 *** |
| | Dwelling is rented out | 0.101 * | 0.112 * | 0.067 | 0.075 |
| | Dwelling is shared | 0.191 *** | 0.195 *** | 0.169 *** | 0.168 *** |
| Location | Municipal sewage | 0.198 *** | 0.261 *** | 0.199 *** | 0.228 *** |
| | Garbage collection | 0.167 *** | 0.141 *** | 0.151 *** | 0.160 *** |
| | Electricity for lighting | 0.211 *** | 0.172 *** | 0.123 *** | 0.114 *** |
| | Distance to paved road (Km) | -0.001 * | -0.000 | 0.002 ** | 0.002 *** |
| | Distance to primary school (Km) | -0.001 * | -0.001 | -0.001 ** | -0.001 * |
| | Mountain area | -0.783 *** | 0.035 | -1.110 *** | -1.162 *** |
| | Hill area | -0.507 *** | -0.110 *** | -0.536 *** | -0.513 ** |
| | Urban area | 0.303 *** | 0.276 *** | -0.051 | -0.007 |
| Neighborhood | District mean rent level (log) | 0.324 *** | 0.982 ** | | |
| | District mean rent squared (log) | | -0.038 * | | |
| | VDC mean rent level (log) | | | 0.554 *** | 1.416 *** |
| | VDC mean rent squared (log) | | | | -0.047 *** |
| | Constant | 1.702 | -2.162 | 0.183 | -3.522 * |
| | Region fixed effects | No | Yes | No | No |
| | District fixed effects | Yes | No | Yes | Yes |
| | Observations | 5,568 | 5,568 | 5,568 | 5,568 |
| | Adjusted R-squared | 0.602 | 0.584 | 0.639 | 0.640 |
| | F-test | 18.2 *** | 4.9 ** | 574.5 *** | 20.8 *** |

*Note*: All regressions were estimated using ordinary least squares with household weights. Statistically significant coefficients at the 10, 5 and 1 percent level are indicated by one, two, and three asterisks, respectively. Joint significance F-tests were performed for neighborhood effects.

Overall, neighborhood effects appear to be strong predictors of self-assessed housing rents. The fit is strongest for specifications in which neighborhood effects are measured at the VDC level and in which their impact is assumed to be quadratic (column four). Therefore, such is the specification retained for the microsimulations.

## 7. Robustness tests

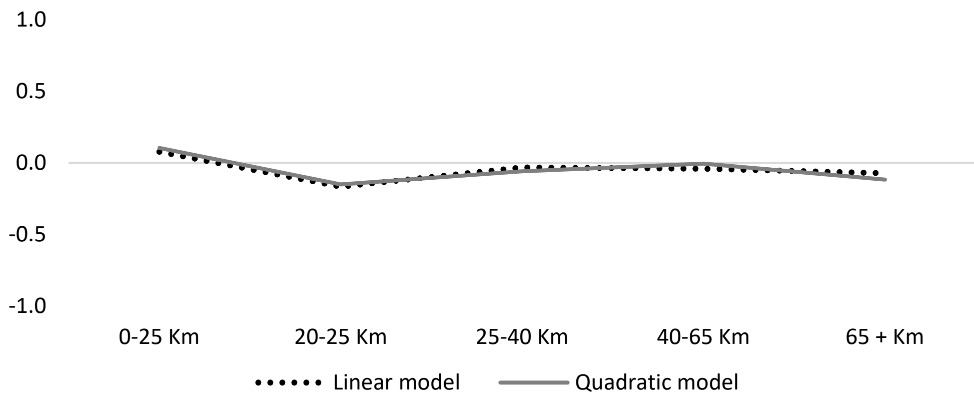
Several robustness tests were run to assess the reliability of the estimated hedonic price function, and especially the stability of the estimated neighborhood effects. Some of the robustness tests focused on the data used, while others concerned the assumptions about the stochastic disturbances in the regression.

Starting with the data, the distribution of observations for each district and VDC was analyzed to ensure that local averages were not influenced by outliers. Second, the regressions were performed again using the self-assessed housing values instead of self-assessed housing rents as dependent variable. Third, for the preferred specification, the estimations were performed separately for several subsamples – including for the bottom 90 and 40 percent of imputed housing prices, as well as for urban and rural areas. Besides, neighborhood effects were also computed based on average household expenditures, rather than average imputed housing prices. The results of these tests, available upon request, all confirm the stability of the regression results – including of the neighborhood effects – presented above.

As for the stochastic disturbances, an important concern is whether they could be spatially correlated. If so, regression results would be biased, much the same as they are in time-series analyses when residuals are serially correlated (Anselin 2003, and Anselin and Rey 2010). To test for possible spatial autocorrelation, consistent with Conley (1999), the three-step approach proposed by Li and Rama (2015) is followed. First, a new variable measuring the log of distance-weighted sum of the neighborhood effects for all other VDCs is added to the preferred empirical specification, either linearly or in quadratic form. Second, correlation coefficients between the residuals of this new regression are computed for every pair of geographic areas. And third, these correlation coefficients are plotted against the distance between the areas considered.

These results suggest that the fit of the regressions and reliability of the estimated coefficients are not affected by spatial autocorrelation. Except for one of the specifications, the coefficients on the log of distance-weighted sum of the neighborhood effects for all other VDCs are statistically insignificant (table A.3). The adjusted $R^2$ coefficients for the regressions remain roughly unchanged as well, providing further evidence that the additional spatial variable does not increase explanatory power much. And all other coefficients fall within the same range as before. Importantly, the residuals of the new regressions are narrowly distributed around zero, with their correlation across pairs of geographic areas being independent of the distance between them (figure 2). This result provides further reassurance that spatial autocorrelation does not bias the results, and in particular the estimated neighborhood effects.

**Figure 2. Correlation between local residuals and distance between localities**




*Note:* The legend indicates the specification chosen for the neighborhood effect. Mean values are computed at the VDC level.

## 8. Microsimulation results

The microsimulations performed are based on an iterative process, using the preferred estimation of the hedonic price function at the household level and measures of actual destruction at the local level. The process involves first evaluating the physical loss of assets each household might have experienced due to the disaster. Then, the monetary damage from this loss is evaluated as if asset prices had not changed, which results in new market values for all dwellings in each locality. A mean of these new market values allows assessing the change in neighborhood effects due to the disaster. Plugging this change in the hedonic price function leads to a second-round impact of the disaster, hence to new market values for dwellings and new neighborhood effects. The computation is repeated until changes become marginal.

More specifically, the first step in this process is to adjust the market value of each dwelling in a way that reflects the physical destruction it might have experienced due to the disaster. In terms of equation (6), the damage term $\left(K_0^h - K_1^h\right)p_0^i$ is assessed by allocating the estimated local destruction rates $\left(K_0^i - K_1^i\right)/K_0^i$ across the households covered by the 2011 NLSS III. Four alternative allocation rules are used to this effect:

*(i)* *Proportional.* The market value of all dwellings in a locality is reduced by a fraction equal to the proportion of houses destroyed in the locality.

*(ii)* *Random.* Households in the locality are drawn randomly from the sample and the market value of their dwellings is set equal to zero. Drawings continue until the cumulative damage matches the proportion of houses destroyed in the locality.

*(iii)* *Cheapest*. Dwellings with the lowest market value are supposed to be destroyed first. Their market value is set equal to zero, continuing until the cumulative damage equals the proportion of houses destroyed in the locality.

(iv) *Weakest.* Dwellings with the weakest foundations – starting with mud, followed by wood, then cement, and finally pillars – see their market values set equal to zero, until matching the proportion of houses destroyed in the locality. The random assignment described above is used for the last group of dwellings affected.

The last allocation rule is the preferred one, with microsimulations based on the other three rules used to assess the robustness of the results. The allocation allows estimating the damage $(K_0^h - K_1^h)p_0^i$ experienced by each individual household, while the subsequent steps in the iterative process described above predict the loss $K_1^h(p_0^i - p_1^i)$. For ease of interpretation, these two components of the cost from the disaster in its aftermath can be expressed as a share of total household expenditure, or as a fraction of the country's GDP (table 2).

**Table 2: Aggregate disaster cost resulting from the microsimulations**

| | Damage | Loss | Total |
|---|---|---|---|
| Percent of household expenditure | 31.4 | 7.3 | 38.7 |
| Percent of GDP | 22.8 | 6.5 | 29.3 |

The overall cost of the Gorkha earthquakes, as estimated using approach proposed in this paper, was very significant: almost 40 percent of annual household expenditures, and close to 30 percent of the country's GDP. While damage accounted for the largest share of this cost, losses still represented about a fifth of the total, suggesting that a narrow focus on physical destruction may lead to substantially underestimate the cost of disasters. Results are similar when relying on the other three allocation rules for the destruction of housing at the local level.

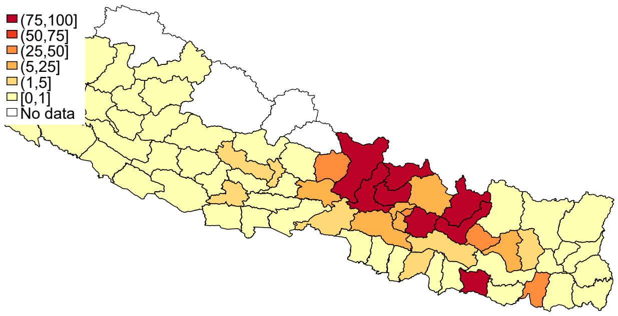
The proposed approach also allows to generate geographically disaggregated estimates of disaster costs. The results show that they are very heavily concentrated in a limited number of districts, especially those around the epicenters, where almost all housing was destroyed (figure 3). In relative terms, losses matter less in these locations, where only a few dwellings were left standing. On the other hand, losses are significant in the Kathmandu valley, which is further away from the epicenters. This varying mix of damages and losses provides further evidence that narrowly focusing on physical destruction can be misleading.

## 9. Comparison with standard estimates

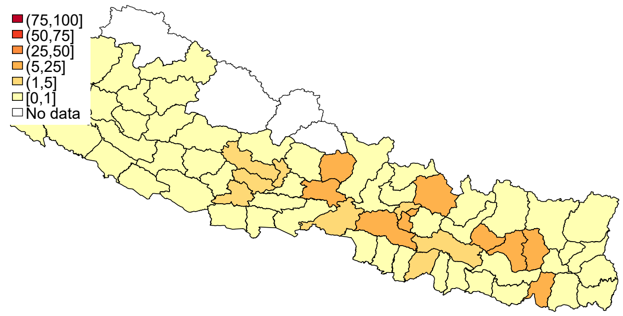
For the 14 districts most affected by the disaster, the cost assessment obtained using the approach proposed in this paper can be compared to that estimated from the PDNA. Overall, the results are within the same order of magnitude. However, discrepancies are significant at the district level. Clearly, they do not arise from the physical destruction of housing, given that the approach used in this paper simply allocates that physical destruction across households, without modifying the total. They rather stem from the way dwellings are valued, both before and after the disaster.

**Figure 3. Total cost is heavily concentrated geographically**

a. Damage




b. Loss




c. Total

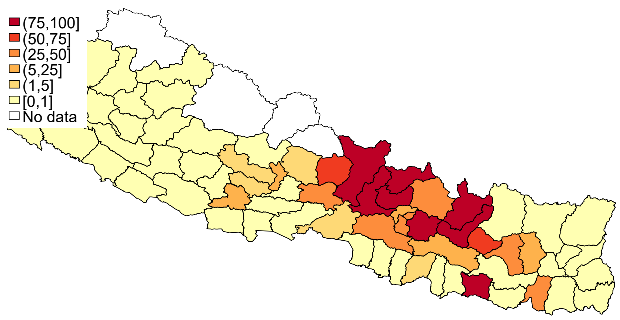
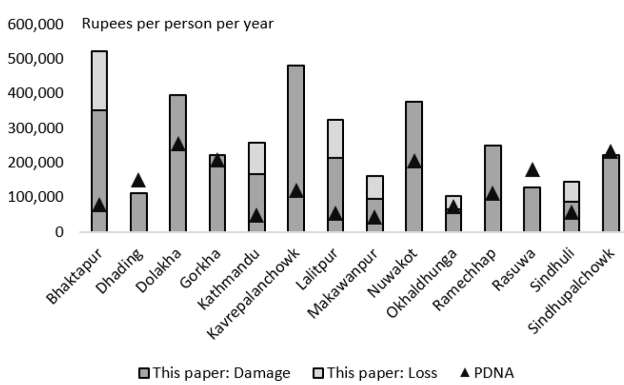
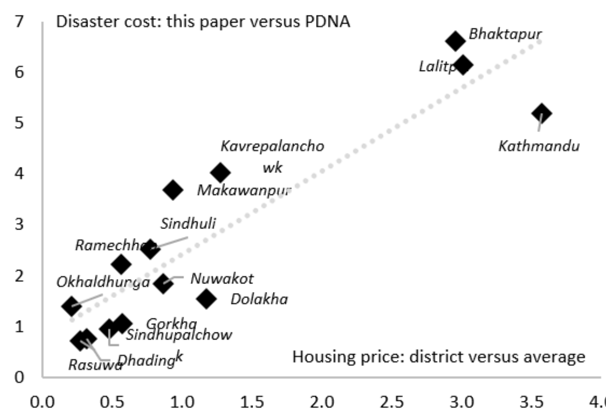



**Figure 4. Housing prices drive discrepancies with previous estimates**

*a.* Estimated costs discrepancies…




*b.* … and their relation to local housing prices




Note: The dotted line in panel b is a linear trend.

For instance, in Dhading district, where most of houses were destroyed, the approach proposed in this paper yields a cost estimate 25 percent lower than that from the PDNA. Conversely, in Kathmandu, where one-tenth of houses were destroyed, the cost estimate from the proposed approach is 3.5 higher than that reported by the PDNA (figure 4.a). This is because the average housing price before the disaster was one-quarter below the national average in Dhading district, but 3.5 times above the average in Kathmandu. Beyond this example, there is a clear correlation between local housing prices and the cost discrepancy between the proposed approach and the PDNA (figure 4.b).

## 10. Conclusion

This paper offers a tractable approach to rapidly estimate the overall cost of a disaster, its decomposition between damage to assets and indirect losses, and its spatial distribution. The proposed approach is light in terms of data collection but rigorous in its conceptual underpinnings. On the empirical front, it relies on data from household expenditure surveys predating the disaster and on some assessment of the housing destruction it triggered at the local level. On the analytical front, it combines insights from poverty analysis and urban economics.

A key tenet of the proposed approach is that the value of dwellings captures not only the comfort they directly provide, but also the access to earnings opportunities and non-monetary amenities they allow. A disaster affects the value of dwellings both by making them less livable – or not livable at all – and by undermining the opportunities and amenities around them. The second key tenet of the proposed approach is that this indirect impact can be captured by estimating hedonic pricing regressions for housing that explicitly incorporate neighborhood effects.

An application of the proposed approach to the 2015 Nepal Gorkha earthquakes shows that it is easy to implement, and yields results that in retrospect look eminently sensible. The overall disaster cost estimated this way is in line with that from standard assessments, whose main focus is on the physical destruction of assets. But the spatial distribution of the cost is substantially different, with potentially important implications for the allocation of post-disaster aid.

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## Table A.1. Relevant variables

| | Variable | Definition | Units |
|---|---|---|---|
| **Dependent** | Self-assessed housing rent | What is the (self-assessed) housing rent? | Nepalese Rupees per year (Log) |
| **Dwelling** | Land plot | What is the size of housing plot? | Ha (Log) |
| | Dwelling area | What is the size of the inside of the dwelling? | sq (Log) |
| | Number of rooms | How many rooms are occupied by the household? | Number |
| | Dwelling has a kitchen | Is there a kitchen in the dwelling? | Dummy |
| | Dwelling has a cement wall | Are dwelling walls in cement? | Dummy |
| | Dwelling has pillar or cement foundation | Is dwelling foundation pillar or cemented? | Dummy |
| | Dwelling has tin or cement roof | Is dwelling roof tin or cementer? | Dummy |
| | Dwelling has windows | Are dwelling windows made of screens/glass? | Dummy |
| | Electricity for lighting | Is the dwelling main source of lighting electricity? | Dummy |
| | Dwelling has piped water supply | Is drinking water coming from piped? | Dummy |
| | Dwelling has piped water | Is the dwelling connected to piped water? | Dummy |
| | Paved road next to dwelling | Is there a paved road next to the dwelling? | Dummy |
| | Year dwelling was built | Which year was the dwelling built? | Year |
| | Dwelling is rented | Is the household paying an actual rent? | Dummy |
| | Dwelling is rented out | Is the household renting the dwelling to someone else? | Dummy |
| | Dwelling is shared | Is the dwelling shared with other households? | Dummy |
| **Location** | Municipal sewage | Is the sanitary system for liquid wastes underground drain? | Dummy |
| | Garbage collection | Is household garbage mainly collected by garbage truck? | Dummy |
| | Distance to paved road | What is the distance to the nearest paved road? | Km |
| | Distance to primary school | What is the distance to the nearest primary school? | Km |
| | Mountain area | Is the dwelling located in a mountain area? | Dummy |
| | Hill area | Is the dwelling located in a hill area? | Dummy |
| | Urban area | Is the dwelling located in an urban area? | Dummy |

## Table A.2. Summary statistics

| Variable | | Units | All districts | Most affected districts | Other districts |
|---|---|---|---|---|---|
| **Dependent** | Self-assessed housing rent (NPR per year) | *Nepalese Rupees per year* | 19,789 | 29,496 | 15,200 |
| **Dwelling** | Land plot | *Ha (Log)* | -4 | -4 | -4 |
| | Dwelling area | *sq (Log)* | 6 | 6 | 6 |
| | Number of rooms | *Number* | 5 | 5 | 5 |
| | Dwelling has a kitchen | *Percent* | 67 | 62 | 70 |
| | Dwelling has a cement wall | *Percent* | 25 | 30 | 23 |
| | Dwelling has pillar or cement foundation | *Percent* | 26 | 31 | 24 |
| | Dwelling has tin or cement roof | *Percent* | 48 | 59 | 43 |
| | Dwelling has windows | *Percent* | 12 | 24 | 7 |
| | Electricity for lighting | *Percent* | 70 | 74 | 68 |
| | Dwelling has piped water supply | *Percent* | 44 | 64 | 34 |
| | Dwelling has piped water | *Percent* | 21 | 34 | 14 |
| | Paved road next to dwelling | *Percent* | 24 | 36 | 19 |
| | Year dwelling was built | *Year* | 2,049 | 2,046 | 2,050 |
| | Dwelling is rented | *Percent* | 8 | 15 | 4 |
| | Dwelling is rented out | *Percent* | 5 | 8 | 4 |
| | Dwelling is shared | *Percent* | 19 | 28 | 15 |
| **Location** | Municipal sewage | *Percent* | 8 | 22 | 1 |
| | Garbage collection | *Percent* | 7 | 14 | 3 |
| | Distance to paved road | *Km* | 14 | 12 | 15 |
| | Distance to primary school | *Km* | 1 | 0.6 | 1.1 |
| | Mountain area | *Percent* | 7 | 8 | 6 |
| | Hill area | *Percent* | 47 | 75 | 34 |
| | Urban area | *Percent* | 20 | 30 | 15 |

*Source: Nepal NLSS III 2010/11*

## Table A.3. Regression for self-assessed rent accounting for spatial autocorrelation

| | Neighborhood effect level<br>Neighborhood effect model | VDC<br>Linear | VDC<br>Quadratic | VDC<br>Linear | VDC<br>Quadratic |
|---|---|---|---|---|---|
| **Dwelling** | Land plot (log Ha) | 0.057 *** | 0.055 *** | 0.058 *** | 0.056 *** |
| | Dwelling area (log sq ft) | 0.238 *** | 0.238 *** | 0.238 *** | 0.239 *** |
| | Number of rooms | 0.114 *** | 0.114 *** | 0.114 *** | 0.115 *** |
| | Dwelling has a kitchen | 0.161 *** | 0.159 *** | 0.160 *** | 0.156 *** |
| | Dwelling has a cement wall | 0.156 *** | 0.160 *** | 0.156 *** | 0.162 *** |
| | Dwelling has pillar or cement foundation | 0.224 *** | 0.228 *** | 0.225 *** | 0.229 *** |
| | Dwelling has tin or cement roof | 0.280 *** | 0.278 *** | 0.276 *** | 0.271 *** |
| | Dwelling has windows | 0.211 *** | 0.219 *** | 0.213 *** | 0.219 *** |
| | Electricity for lighting | 0.123 *** | 0.114 *** | 0.121 *** | 0.111 *** |
| | Dwelling has piped water supply | 0.031 | 0.035 | 0.0296 | 0.035 |
| | Dwelling has piped water | 0.131 *** | 0.132 *** | 0.130 *** | 0.135 *** |
| | Paved road next to dwelling | 0.120 *** | 0.140 *** | 0.121 *** | 0.139 *** |
| | Year dwelling was built | 0.001 | 0.001 | 0.001 | 0.001 |
| | Dwelling is rented | -0.306 *** | -0.298 *** | -0.305 *** | -0.298 *** |
| | Dwelling is rented out | 0.067 | 0.075 | 0.068 | 0.073 |
| | Dwelling is shared | 0.169 *** | 0.168 *** | 0.168 *** | 0.167 *** |
| **Location** | Municipal sewage | 0.199 *** | 0.228 *** | 0.204 *** | 0.213 *** |
| | Garbage collection | 0.151 *** | 0.160 *** | 0.157 *** | 0.157 *** |
| | Distance to paved road (Km) | 0.002 ** | 0.002 *** | 0.002 ** | 0.002 ** |
| | Distance to primary school (Km) | -0.001 ** | -0.001 * | -0.002 ** | -0.002 * |
| | Mountain area | -1.110 *** | -1.162 *** | -1.389 *** | -1.426 *** |
| | Hill area | -0.536 *** | -0.513 ** | -0.822 *** | -0.723 *** |
| | Urban area | -0.051 | -0.007 | -0.054 | -0.012 |
| **Neighborhood effect** | VDC mean rent level (log) | 0.554 *** | 1.416 *** | 0.556*** | 1.441 *** |
| | VDC mean rent squared (log) | | -0.047 *** | | -0.048 *** |
| **Spatial control** | Distance-weighted sum of neighborhood effect for all other VDCS level (log) | | | -1.948 | -51.17 ** |
| | Distance-weighted sum of neighborhood effect for all other VDCS squared (log) | | | | 4.962 ** |
| | Constant | 0.183 | -3.522 * | 0.561 | -3.186 |
| | Region fixed effects | No | No | No | No |
| | District fixed effects | Yes | Yes | Yes | Yes |
| | Observations | 5,568 | 5,568 | 5,544 | 5,544 |
| | Adjusted R-squared | 0.639 | 0.64 | 0.64 | 0.64 |
| | F-test | 574.5 *** | 20.8 *** | 573.7 *** | 21.5 *** |

*Source:* Own estimates using the NLSSIII.

*Note:* All regressions use household weights. Statistically significant coefficients at the 10, 5 and 1 percent level are indicated by one, two, and three asterisks, respectively. Joint significance tests (in the form of an F test) are performed for the neighborhood effects. OLS stands for ordinary least squares.