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Measuring the Welfare Effects of Slum Improvement Programs: The Case of Mumbai

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Abstract

This paper evaluates the welfare effects of in-situ slum upgrading and relocation programs using data for 5,000 households in Mumbai, India. We estimate a model of residential location choice in which households value the ethnic composition of neighborhoods and employment accessibility in addition to housing characteristics. The importance of neighborhood composition and employment access implies that relocation programs must be designed carefully if they are to be welfare-enhancing. The value of our model is that it allows us to determine the magnitude of these effects. It also allows us to determine the value households place on in situ improvements, which policymakers need to know if they are to design housing programs that permit cost recovery.

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I. Introduction

Slums, which are characterized by substandard housing and inadequate water and sanitation facilities, present some of the most pressing urban environmental problems in developing countries. Overcrowding and unsanitary conditions increase the incidence of communicable diseases, such as diarrhea, worms, and tuberculosis, and make infant mortality rates in slums almost as high as in rural areas (Sclar, Gareau and Carolini [24]). This is due both to poor healthcare and unsanitary conditions: water quality in slums is poor and community toilets often overflow with human waste.

In the early Twentieth Century, slum improvement programs in many countries were equivalent to slum clearance—hardly a solution to the problem of lack of adequate housing in developing country cities. Beginning in the 1970's the strategy shifted to one of improving and consolidating existing housing—often by providing slum dwellers tenure security, combined with the materials needed to upgrade their housing or—in areas where land was plentiful—to build new housing. Emphasis on in situ improvements has continued to the present. These improvements may take the form of providing infrastructure services and other forms of physical capital, but also include efforts to foster community management, and access to health care and education. At the same time, some have called for replacing slums with multiple story housing either at the site of the original slum or in an alternate location.

The goal of this paper is to evaluate the welfare effects of such programs using data for Mumbai (Bombay), India. A key issue in slum upgrading is whether current residents are made better off by improving housing in situ, or by relocating. The answer to this question depends on the tradeoffs people are willing to make taking account of commuting costs, housing costs and the attributes of the housing that they consume. If, for example, a relocation program distances a worker from his job and, if finding a new job is difficult, in situ improvements in housing may dominate relocation programs. The utility of relocation programs also depends on neighborhood composition: if households depend on neighbors of the same caste or ethnic group for information about employment or for social services, relocation to neighborhoods of different ethnicity may be welfare-reducing.

Evaluating the welfare effects of slum upgrading and resettlement programs can be accomplished by estimating models of residential location choice, in which households trade off commuting costs against the cost and attributes of the housing they consume, including neighborhood attributes. We estimate such a model using data for 5,000 households in Mumbai, a city in which 40% of the population lives in slums. A key feature of Mumbai that distinguishes it from other Third World cities is that many slums are centrally located, i.e., located near employment centers, rather than being relegated to the periphery of the city. Slum relocation projects may therefore involve moving people to more remote locations. We ask what corresponding improvements in housing and/or income would be necessary to offset the location change.

To answer these questions we estimate a model of residential location choice for households in Mumbai. The choice of residential location is modeled as a discrete choice problem in which each household's choice set consists of the chosen house type plus a random sample of 99 houses from the subset of the 5,000 house types in our sample that the household can afford. House types are described by a vector of housing characteristics and by the characteristics of the neighborhood within a 1 km radius. Two important neighborhood characteristics are ethnic composition (the percent of one's neighbors of the same religion and same mother tongue) and employment accessibility. In one specification we treat the employment location of the primary household earner as fixed and characterize house types by their distance from the current work location. In an alternate specification we replace distance to the current workplace by an employment accessibility index, to capture opportunities for changing jobs.

We use the model of residential location to examine the welfare effects of specific programs—in situ improvements in housing attributes and the provision of basic public services, and a slum relocation program. Historically, both types of programs have been implemented in Mumbai (Mukhija [21]; Mukhija [22]). In 1985 the World Bank launched the Bombay Urban Development Project to provide tenure security and encourage in situ upgrading by slum dwellers. In the same year the Prime Minister's Grant Project (PMGP), introduced by the state of Maharashtra, proposed to construct new housing units on the sites of existing slums in Dharavi. Currently the Valmiki Ambedkar Awas Tojana Program (VAMBAY) provides loans to the poor to build or upgrade houses.[1]

The economics literature on the benefits of slum improvements has, for the most part, consisted of hedonic studies that estimate the market value of various improvements, including tenure security and infrastructure services (Crane et al. [10]; Jimenez [13]). Kaufman and Quigley [14] advanced this literature by estimating the parameters of household utility functions rather than limiting the analysis to the hedonic price function. We extend this literature in three ways: first, following Bayer, McMillan

[1] http://mhada.bom.nic.in/html/web_VAMBAY.htm. Mukhija (2001) notes that there was little interest in the World Bank's 1985 program, possibly due to competition from the Prime Minister's Grant Project.

and Rueben [2,3] we introduce distance to work and neighborhood amenities—in particular the language and religion of one's neighbors—as factors influencing the choice of residential location. One advantage of the discrete choice approach over the hedonic approach to modeling residential location is that the former more easily incorporates characteristics that vary with the chooser, such as the distance to his workplace. It also allows the value of neighborhood characteristics—for example, religion or language—to depend on household attributes: A Hindu household may value living with Hindus more than living with Muslims. Secondly, we account for unobserved heterogeneity in housing and neighborhood attributes, in the spirit of Bayer, McMillan and Rueben [3], by estimating housing-type constants for all housing types in the universal choice set. Failure to do so will bias the values attached to housing and neighborhood attributes. Thirdly, we extend Bayer, McMillan and Rueben [2,3] by computing exact welfare measures for changes in housing and neighborhood attributes.[2]

The paper is organized as follows. Section 2 describes the data used in our empirical work and presents the stylized facts about where people live and work in Mumbai. Section 3 describes the model of residential location choice. Section 4 presents estimation results and section 5 the welfare effects of slum upgrading policies. Section 6 concludes.

II. Job and Housing Locations in Mumbai

The target population of our study are households in the Greater Mumbai Region (GMR), which constitutes the core of the Mumbai metropolitan area. The GMR, with a population of 11.9 million people in 2001, is one of the most densely populated cities in

[2] The purpose of Bayer et al.'s analysis is not to value specific policy measures but rather to uncover the importance of different factors in explaining neighborhood segregation.

the world.[3] Located on the Arabian Sea, the GMR extends 42 km north to south and has a maximum width of 17 km. The Municipal Corporation of Greater Mumbai has divided the city into 6 zones (see Figure 1), each with distinctive characteristics.[4] The southern tip of the city (zone 1) is the traditional city center. Zone 3 is a newly developed commercial and employment center, and zones 4, 5 and 6, each served by a different railway line, constitute the suburban area. In the remainder of this section we describe the distribution of population and jobs in the GMR, as well as the characteristics of the housing stock, based on a random sample of 5,000 households in Mumbai who were surveyed in the winter of 2003-2004 (Baker et al. [1]).[5]

Table 1 presents our sample households, broken down by income category. Households earning 5,000 Rs. per month or less constitute the bottom quartile (26.5%) of our sample, households earning 5,000-7,500 Rs. per month the next quartile (27.7%), households earning 7,500-10,000 Rs. per month 22% of our sample, and households in the next two income categories 18% and 6% of our sample, respectively.[6]

[3] The population density of Mumbai in 2006 was about 27,220 persons per km2.

[4] The shaded areas in Figures 1-3 represent parks and flood plains—portions of the city that are not inhabited.

[5] The sampling universe for the Mumbai survey was the Greater Mumbai Region (GMR). All households in the city were part of the sampling universe with the exception of residents of military cantonments and institutional populations (e.g., prisons). The target sample size was 5,000 households. Household listings from the March 2001 Census were used as a sampling frame. To ensure that all parts of the city were covered by the sample, we chose sample fractions in each of 88 sections of the city in proportion to population. Within each section census enumeration blocks (CEBs) were randomly selected in proportion to population. Approximately 1,000 CEBs were sampled, with (on average) 5 households chosen in each CEB. The selection of the households to be interviewed within a CEB was determined by choosing an arbitrary starting point in the CEB and sampling every 10^{th} household. The respondent within each household was either the head of household or the head's spouse. Enumerators were instructed to alternate male and female respondents within an enumeration block to assure an equal number of male and female respondents.

[6] In PPP terms, 5,000 Rs. corresponds to $562 USD.

Almost 40% of our sample households live in slums, with the percent living in slums increasing as income falls.[7] This number is consistent with the extent of slums in other cities (United Nations Global Report on Human Settlements [26]). According to the United Nations, 924 million people, or 31.6% of the world's urban population, lived in slums in 2001. Slums in Mumbai were formed by residents squatting on open land as the city developed.[8] Slum residents do not possess a transferable title to their property; however, "notified" squatter settlements have been registered by the city, and slum dwellers in these settlements are unlikely to be evicted.[9] Chawls, which house approximately 35% of sample households, are usually low-rise apartments with community toilets that, on average, have better amenities than slums. The remaining 25% of households live either in cooperative housing, which includes modern, high-rise apartments, in bungalows, or in employer-provided housing.

Because slum upgrading is the focus of the paper, Table 2 presents the characteristics of our sample households who reside in slums. The table confirms that slum households are quite heterogeneous. Although 37% of slum households fall in lowest income category, 29% have incomes of 7,500 Rs. per month or more. Similarly, although 60% of households have a main earner who is either a skilled or unskilled laborer, a significant fraction of households have a main earner who is a white-collar

[7] Throughout this paper the term "slum" and "squatter settlement" are used interchangeably. In the household survey 40% of residents live in squatter settlements. Virtually all squatter settlements in Mumbai would be classified as slums.

[8] For example, Dharavi, the world's largest slum, was originally a fishing village located on swamp land. Slums began forming there in the late 19th century when land was reclaimed for tanneries. Once on the periphery of Mumbai, Dharavi is now centrally located (in zone 2).

[9] 1.8 % of our sample households live in "non-notified" slums and 1.6 % in resettlement areas. The average tenure of households in notified squatter settlements suggests that squatters are unlikely to be evicted: 81% of households have been living in current location for more than 10 years while corresponding figure for the formal housing sector is 74%.

worker and 17% of main earners have more than a high school education. Thus, although a significant fraction of slum dwellers are poor, all are not.[10]

A. Distribution of Population and Housing

The spatial distribution of sample households by housing type is shown in Figures 2 and 3, where each dot represents 5 households, and is summarized in Table 3. Slums are not evenly spread throughout the city: they constitute a higher-than-average fraction of the housing stock in zones 5 and 6 (79% and 47%, respectively), but less than 20% of the housing stock in zones 1 and 4. Nonetheless, slum dwellers in Mumbai are considerably more integrated among non-slum dwellers than in other cities: 40% of slum-dwellers live in central Mumbai (zones 1-3).[11] In contrast, there are virtually no slums in central locations in Delhi or many cities in Latin America (United Nations Global Report on Human Settlements [26], Ingram and Carroll [12]). In these cities, slums are typically located at the periphery: as a consequence, slum dwellers may spend several hours commuting to work.

Table 4 shows characteristics of the housing stock by housing type and zone. It attests to the fact that slum dwellings are, on average, smaller than either chawls or cooperative housing, and less likely to have piped water connections or a kitchen inside the dwelling. It is, however, the case that the quality of slum housing varies considerably by zone: whereas 61% of slum households have piped water in zone 2, only 19% of slum households have piped water in zone 4 (Baker et al. [1], Table 37).

Two features of Tables 1 and 4 deserve comment. Table 1 suggests that households in Mumbai are less mobile than households in the U.S. This is true of most developing country cities and is due, in part, to a thin mortgage market. In most

[10] As a referee has noted, this heterogeneity is necessary if we are to identify our residential location model.
[11] This is also true of the poor v. the non-poor. See Baker et al. [1] Figure 2 and Tables 2 and 3.

developed countries, the ratio of outstanding mortgage loans to GDP is between 0.25 and 0.60. In India mortgages were 2.5% of GDP in 2001.[12] Table 4 reveals the very small floor space enjoyed by households in Mumbai. (The average floor space in Table 4 corresponds to a room 16 feet by 16 feet.) This is largely the result of building height restrictions which limit the amount of floor space constructed per unit of land (Bertaud [7]).

B. Distribution of Jobs and Commuting Patterns

Table 5, based on data for 6,371 workers in our sample households, shows where people living in each zone work.[13] Fifty-seven percent of workers in our sample households work in zones 1-3, 31% in the suburbs (zones 4-6), and 6% at home. The rest either do not work in a fixed location or work outside of the GMR. A striking feature of Table 5 is the high percent of workers who live in the same zone in which they work. This is highest in zones 1-3, but is substantial even in the suburbs. Replicating Table 5 for different income and occupational groups reveals that the diagonal elements in the table (the percent of people working and living in the same zone) are higher for workers in low-income than in high-income households, and are higher for unskilled and skilled laborers than for professionals (Baker et al. [1], Tables 38 and D-1).

Figure 4, which shows the distribution of one-way commute distances for workers in our sample is consistent with Table 5: the median journey to work is less than 3 kilometers, although the distribution of commute distances has a long tail. Table 6, which shows mean commute distance by zone and income, suggests that persons with longer commutes are more likely to live in the suburbs, especially in zones 4 and 6. With

[12] http://www.economywatch.com/mortgage/india.html
[13] Table 4 is based on the usual commutes of the two most important earners in each household. Forty percent of sample households have more than one earner.

few exceptions, mean commute to work increases with income, regardless of zone of residence.

The information presented here suggests that, on average, people in Mumbai live close to where they work: This is especially true for the poor, and also for laborers. This suggests that households may place a high premium on short commutes.[14] If, in the short run, workers' job locations are fixed, slum upgrading programs that require households to move may reduce welfare if they move workers farther from their jobs. The impact of such programs on welfare will, however, also depend on the value attached to housing and neighborhood amenities.

III. Analytical Framework

The models of residential location choice we have estimated are descendants of discrete location choice models (e.g., McFadden [17]), but incorporate the recent literature on the treatment of unobserved heterogeneity in discrete location choice models (Bayer, McMillan and Rueben [3]). This section describes in detail the structure of these models and how they will be used to evaluate slum improvement programs.

A. Modeling Location Choice

We characterize housing types in Mumbai by a vector $\boldsymbol{X_h}$ of house characteristics, by the religion and language of the neighborhood in which the house is located and by an index of employment accessibility.[15] We assume that the utility that household i receives from house type h depends on $\boldsymbol{X_h}$ and on the interaction of the household's religion (language) and that of the neighborhood. Formally, let Z_{ri} = 1 if household i is of the religion r and = 0 otherwise. $\boldsymbol{R}_{rh,}$ is a 1 x J vector of dummy

[14] A similar result is reported by Mohan [20] in his study of Bogota and Cali, Colombia: the average commute distance of workers in Bogota in 1978 is approximately 4 km.
[15] Formally, we assume that the house inhabited by each household in our sample represents a housing type, and that there are many houses of the same type in Mumbai. Given the size of our sample (5,000 households) relative to the number of households in Mumbai (over 3 million), this is a reasonable assumption.

variables describing the distribution of religion r in the neighborhood in which h is located. (For example, R_{r1h} equals 1 if <1% of the neighborhood is of religion r, R_{r2h} equals 1 if 1-5% of the neighborhood is of religion r and so forth.) Household i's utility depends on the interaction of its religion with the elements of $\boldsymbol{R}_{rh}$ and likewise for language ($\boldsymbol{L}_{lh}$). Utility also depends on the employment accessibility of the principal earner in the household, E_{ih}, and on expenditure on all other goods, i.e., on income y_i minus the user cost of housing, p_h. Formally,

$$U_{ih} = \boldsymbol{\beta_X X_h} + \sum_r \sum_j \alpha_j Z_{ri} R_{rjh} + \sum_l \sum_j \gamma_j Z_{li} L_{ljh} + \beta_E E_{ih} + \beta_p \ln(y_i - p_h) + \xi_h + \varepsilon_{ih} \qquad (1)$$

In (1) ξ_h is a house specific constant that captures unobserved house and neighborhood characteristics that are perceived identically by all households; ε_{ih} captures unobserved housing characteristics as perceived by household i. The terms in the first double summation are all zero except for the percent of the neighborhood that is of same religion as the household. Our specification—i.e., the fact that α varies only with j and not r—assumes that Muslims receive the same utility from having >75% of the neighborhood Muslim as Hindus do from having >75% of the neighborhood Hindu.

Estimation of the parameters of (1) will allow us to infer the rate of substitution between accessibility to work and housing cost, and accessibility to work and neighborhood and housing characteristics. To evaluate the welfare effect of moving household i from its chosen location to a new one, we compute the amount, CV, that must be subtracted from the Hicksian bundle to keep the systematic part of the household's utility constant when it is moved.

C. Estimation of the Model

In estimating the model of residential location choice each household's choice set C_i consists of the chosen house type plus a random sample of 99 house types from the subset of the 4,023 house types in our sample that the household can afford.[16] Estimation of the parameters of (1) follows the two-step approach outlined in Bayer, McMillan and Rueben [3]. For purposes of estimation it is convenient to rewrite equation (1) as

$$U_{ih} = \delta_h + \sum_r \sum_j \alpha_j Z_{ri} R_{rjh} + \sum_l \sum_j \gamma_j Z_{li} L_{ljh_E} + \beta_E E_{ih} + \beta_p \ln(y_i - p_h) + \varepsilon_{ih} \equiv \delta_h + \mu_{ih}(\theta) + \varepsilon_{ih} \quad (2)$$

where $\delta_h \equiv \boldsymbol{\beta_X X_h} + \xi_h$ is the housing-type-specific constant attached to housing type h. In the first step we estimate the parameters in (2)—the set of house-type specific constants $\{\delta_h\}$ and $\boldsymbol{\theta}$ the vector of parameters ($\{\alpha_j\}$, $\{\gamma_j\}$, β_E and β_p) on variables that vary by both household and house type. In the second stage we regress δ_h on $\boldsymbol{X_h}$ to estimate the parameter vector $\boldsymbol{\beta_X}$.

In stage one of the estimation the probability that household i purchases house type h is given by

$$P_{ih} = \frac{\exp[\delta_h + \mu_{ih}(\theta)]}{\sum_{m \in C_i} \exp[\delta_m + \mu_{im}(\theta)]} \quad (3)$$

We find the vector $\boldsymbol{\theta}$ that maximizes the likelihood function for a given value of $\{\delta_h\}$ and calculate the estimated demand for each house h as

$$D_h = \sum_i P_{ih} .$$

Then we search for the set of $\{\delta_h\}$ that satisfy the maximization condition in equation (4), given our estimate of $\boldsymbol{\theta}$,

$$\partial \ln L / \partial \delta_h = (1 - P_{hh}) + \sum_{i \neq h} P_{ih} = 1 - \sum_i P_{ih} = 0, \ \forall h . \quad (4)$$

[16] The original set of approximately 5,000 households is reduced because information about housing characteristics is missing for some houses, and because we eliminate employed-provided housing from the choice set. A house is affordable to household i if its monthly cost does not exceed household i's income.

Berry [5] and Berry, Levinsohn, and Pakes [6] show that for any $\boldsymbol{\theta}$ the unique $\{\delta_h\}$ that satisfy above conditions can be obtained by solving the contraction mapping

$$\delta_h^{t+1} = \delta_h^t - \ln(\sum_i P_{ih}) . \tag{5}$$

where t indexes the t-th iteration of the estimation. The $\{\delta_h\}$ thus obtained are used to re-estimate $\boldsymbol{\theta}$. The procedure is iterated until our estimators converge.

In the second step of the estimation δ_h is regressed on $\boldsymbol{X_h}$ to determine the coefficient vector $\boldsymbol{\beta_X}$. When Bayer et al. [3] estimate discrete models of residential location choice they instrument for house price and also for neighborhood characteristics in the second stage of the estimation. We do not need to do this. House price enters our model as the log of the Hicksian bundle, $ln(y_i\text{-}p_h)$, hence we are able to estimate its coefficient in the first stage of the analysis while controlling for the housing-type specific constants. The same is true of neighborhood characteristics. Our neighborhood characteristics—the language and religion of the neighborhood—enter the utility function multiplied by dummies for the household's own language and religion, so that these coefficients can also be estimated in the first stage.

IV. Estimation Results

A. Specification of the Utility Function

We assume that a household's utility from its residential location [eq. (1)] depends on housing and neighborhood characteristics. The first ten variables in Table 7 describe the house itself: whether the dwelling is a slum or a cooperative (chawl is the omitted category), whether it is a multi-story dwelling (flat), dummy variables to indicate the quality of the floor and roof, and the interior space in square feet. This is followed by a series of dummy variables indicating whether the house has a kitchen, a toilet, or a bathroom (i.e., a room for washing), and whether there is a piped water connection in the house. Due to the high correlation among these housing characteristics we replace them in empirical work by their first two principal components, which have eigenvalues greater than one.[17] We also characterize the house type in terms of distance from the nearest railroad track (whether it is < 300m from a track) and by the zone in which it is located.[18]

Neighborhood characteristics include religion and mother tongue. Specifically, we assume that utility is a function of the percent of households in the neighborhood that (a) are of the same religion as the household in question and (b) who speak the same mother tongue.[19] These variables should capture network externalities and other forms of social capital provided by neighbors of the same ethnic background. Table 7 indicates the degree of ethnic sorting in Mumbai: For example, while Muslim households comprise only 17% of the city's population, the average Muslin household in our sample lives in a neighborhood that is 35% Muslim. Although people from the state of Gujarat constitute only 12% of the population of Mumbai, the average household from Gujarat in our sample lives in a neighborhood that is 26% Gujarati. The extent of ethnic sorting is greater, in relative terms, for minority groups—e.g., for Sikhs, Christians, Buddhists, Tamils and Telugus—than for households in the majority (i.e., Hindus or households that speak Marathi or Hindi). For this reason, we allow the coefficient on ethnic composition to vary with the percent of one's neighbors from the same background.

Employment access (E_{ih}) for the principal wage earner in the household is computed as follows. In Model 1, access is measured by the distance from the location of

[17] The first two principal components explain approximately 60% of the variance in housing attributes.
[18] The results in Tables 8 and 10 change little if zone dummies are replaced by section dummies. (There are 88 sections in Mumbai.) We report results using zone dummies for ease of interpretation.
[19] Neighborhood characteristics are computed using sample households within 1 km of each house. A neighborhood contains, on average, 67 sample households, although the number varies depending on the population density of the area.

house type h to the worker's current job location.[20] The weight attached to distance from the current job location should capture the disutility of relocating in the short run, before the worker can change jobs. In Model 2, we replace distance to the current job from house type h by the average distance from h to the 100 nearest jobs in the worker's occupation, based on our survey data. We distinguish five occupations in computing the employment accessibility index: unskilled workers, skilled workers, sales and clerical workers, small business owners, and managers/professionals. This variable should capture the disutility of being moved away from desirable employment locations, even if the worker can change jobs.

Utility also depends on the log of monthly household income minus the cost of housing (i.e., the log of the Hicksian bundle). The Hicksian bundle is calculated as follows. All sample households were asked what "a dwelling like theirs" would rent for and what it would sell for.[21] We use the stated monthly market rent as the cost of the dwelling. In calculating the income of households who currently own their home, we add to household income from earnings and other sources the monthly rent associated with the dwelling they own. For renters, household income is stated income from earnings and other sources.[22] The mean value of the Hicksian bundle, evaluated at the current residence, is 8,275 Rs. The median Hicksian bundle approximately 6,250 Rs. per month.

[20] The distance from house type h to a worker's job is estimated as the distance between h (whose location is geo-reference in the survey) and the approximate work location. The work location is approximated by the centroid of the intersection of the section and pin code in which the job is located.

[21] It should also be noted that all households, including those in slums, reported a positive answer to this question. (The mean reported rent for slum dwellers is Rs. 1065.) We have used the answers to these questions to compute for each household the interest rate that would equate the purchase price of the house to the discounted present value of rental payments. The mean interest rate is 5.6% and the median 4.8%. Additional evidence that stated market rents are reliable is provided by using them to estimate an hedonic price function for housing in Mumbai. The housing and neighborhood characteristics in Table 7, together with distance to the CBD, explain 64% of the variation in monthly rents in our sample. (See Table A1.)

[22] Seventy-four percent of sample households claim to own their own home, whereas 26% indicate that they rent. Surprisingly, 83% of households living in notified squatter settlements claim to own their own homes, although it is unlikely that they possess a transferable title.

B. Results

Table 8 presents the results of estimating our models. The top of the first column of the table presents estimates of the parameter vector $\boldsymbol{\theta}$, which contains the coefficients of all variables that vary by household as well as by house type and is estimated in the first stage of the estimation procedure together with the set of house-specific constants $\{\delta_h\}$. In the second stage, the $\{\delta_h\}$ are regressed on the principal components of housing characteristics, as well as the zone dummies and whether h is within 300 m of a railroad track. The coefficients from stage two are presented at the bottom of the first column.

The second column of the table presents the coefficients of the individual housing attributes, as well as the marginal value of each amenity, i.e., the marginal rate of substitution between the amenity and the Hicksian bundle, evaluated at the median household income for our sample (6,250 Rs. per month).[23] The coefficients of the k individual housing attributes are derived from the first two principal components as follows. Let $\boldsymbol{A}$ be a k x p (p=2) matrix whose columns contain coefficients of the 2 principal components used in our analysis. Let $\boldsymbol{\beta_p}$ be a p x 1 vector of coefficients on the principal components estimated during stage 2 of the estimation procedure and $\boldsymbol{\beta_x}$ be a k x 1 vector of coefficients on the original k housing characteristics in the utility function. We solve for $\boldsymbol{\beta_x}$ using $\boldsymbol{\beta_x} = \boldsymbol{A\beta_p}$.

In both specifications all housing attributes are statistically significant at the 5% level. Other things equal, being in a chawl (the omitted housing category) is worth about 400 Rs. per month more than being in a slum, whereas being in a coop is worth about 700 Rs. more than being in a chawl. Being in a high-rise building (flat) is worth about 730 Rs. per month. The mean value of a piped water connection is about 240 Rs. per month,

[23] The marginal rate of substitution between (e.g.) E_{ih} and the Hicksian bundle is given by $\beta_E(y_i - p_h)/\beta_H$.

and mean willingness to pay for a private toilet about 580 Rs. per month. Overall, the value attached to housing attributes seems reasonable, with the exception of “good floor.”

Workers in Mumbai place a premium on living close to where they work. Model 1 suggests that a household with income of 6,250 Rs. per month would give up about 330 Rs. to decrease the main earner’s one-way commute by 1 km.[24] In Model 2, the value of a one km decrease in the average distance to the 100 nearest jobs in one’s occupation is 283 Rs.

Neighborhood attributes matter. The value of being with households who speak the same mother tongue and have the same religion depends on whether one is in the minority or the majority. In a neighborhood where only 5-10% of one’s neighbors speak the same mother tongue, the value of a one percentage point increase in mother tongue is large (162 Rs.). [All values refer to model 1.] In a neighborhood where 50-75% of one’s neighbors speak the same mother tongue, the value of a one percentage point increase is only 15 Rs. Similar results hold for living with members of the same religion: a one percentage point increase in the percent of households of the same religion is worth 178 Rs. evaluated at a baseline of 5-10% but is worth only 13 Rs. in a neighborhood where 50-75% of households are already of the same religion.

These values are large, and may reflect various forms of network externalities. Munshi and Rosenzweig [23] emphasize the importance of networks, formed along caste lines, in determining the jobs available to workers in Mumbai. These networks are especially important for laborers and unskilled workers. Similarly, in the United States,

[24] Takeuchi, Cropper and Bento [25] estimate a commute mode choice model in which the mean value of out-of-vehicle travel time is between 35 and 40 Rs. per hour. At a walking speed of 4 km per hour, this implies that the value of reducing one’s commute by 2 km (roundtrip) per day would be between 385 and 440 Rs. per month, assuming 22 work trips. When the distance of the second main earner’s commute is included in the model, the value of a one km decrease in the second earner’s commute is about 300 Rs. per month.

Bayer, Ross and Topa [4] find significant evidence of informal hiring networks, based on the fact that individuals residing in the same block group are more likely to work together than those in nearby but not identical blocks.

In addition to providing employment networks, neighborhoods also serve as social capital to mitigate the effects of poverty. For example, social networks make possible the creation of spontaneous mechanisms of informal insurance and can improve the efficiency of public service delivery and/or of public social protection systems (Collier [9]).

We should, however, be cautious in interpreting these effects. In reality it is virtually impossible to disentangle the different reasons why similar individuals live in the same neighborhood.[25] Part of this sorting is indeed due to preferences. However, neighborhood composition could also be a result of imperfections in housing markets that segregate individuals to specific neighborhoods.

Other amenities that affect residential location are proximity to a railroad track as well as the zone dummies. Living next to a railroad track can be dangerous, in addition to providing visual disamenities: Approximately 6 people are killed each day crossing railroad tracks in Mumbai. The impact of zone dummies varies with the measure of employment access.

V. Evaluating Slum Improvement Programs

The set of policies that have been employed to improve the welfare of slum dwellers is diverse (Field and Kremer [11]; Mukhija [21]). Some projects have focused on providing secure tenure, on the grounds that this will provide an incentive for slum

[25] Ethnic sorting does not appear to reflect the fact that people of the same religion or mother tongue have common educations and incomes. When we attempt to use income and education to explain variation in the exposure of households in minority groups to members of their group, F statistics are rarely significant.

dwellers to invest in housing (Jimenez [13]; Malpezzi and Mayo [18]). Other projects, such as those implemented under the World Bank's Sites-and-Services program (Kaufmann and Quigley [14; Buckley and Kalarickel [8]) have combined secure tenure with provision of basic infrastructure services (piped water and electricity) and loans to allow slum dwellers to themselves build/upgrade their housing.[26] More recently, greater emphasis has been placed on providing incentives for community management and maintenance, including constructing or rehabilitating community centers, and on improving access to health care and education.

In this paper, we focus on improving the physical aspect of slums by providing infrastructure services and improving housing quality. In Mumbai, virtually all slum dwellers have access to electricity; however, only half have piped water. Slum housing consists of small, dilapidated shacks with poor roofs. Programs to improve the physical quality of housing could involve in situ improvements or could involve housing reconstruction, either at the site of the original slum or in a location where bare land is available.

We evaluate stylized versions of both types of programs—in situ upgrading and relocation of slum households to better housing. We focus on slum households located in zone 5, specifically households in sections 79 and 80 who are located within one mile of the Harbor Railway. The characteristics of our sample households living in these slums appear in Table 9. These households are, on average, much poorer than our sample as whole, although 85% claim to own their own home. Average house size is small—141 sq. ft. in section 79 and 162 sq. ft. in section 80. Almost no houses have good roofs and

[26] In the World Bank sites-and-services project in El Salvador evaluated by Kaufman and Quigley [14], slum dwellers were given financing to purchase lots on which infrastructure services were provided, as well as materials to construct new homes. Imperfections in credit markets and in the provision of infrastructure services are major reasons for initiating slum improvement projects.

only one quarter have piped water connections. The primary earner in households in both sections commutes, on average, 5 km to work (one-way), although the variance in commute distance is large. In terms of language and religion, the majority of households in section 79 are Marathi-speaking Hindus. In section 80, the majority of households speak Hindi; sixty percent are Hindus and one-third are Muslims.

The in situ program provides good roofs and piped water connections for households that do not have them. The relocation program moves households from their current locations to new housing in Mankurd, a neighborhood in zone 5 where some households displaced by transportation improvement programs have been relocated.[27] (The original locations of households and the relocation site are shown in Figure 5.) We assume that households are moved into good quality, low-rise buildings with piped water but with community toilets. We assume in the short run that workers in resettled households continue to work in their old job locations. The religious makeup of the new neighborhood is approximately half Hindu and half Muslim. Sixty percent of households speak Hindi and one-third speak Marathi.

To compute the welfare effects of each program, we calculate for each household the amount of money that can taken away from the household, in exchange for the vector of program attributes, to keep the systematic portion of the household's utility constant. Compensating variation (CV) is implicitly defined as:

$$\boldsymbol{\beta}_X \boldsymbol{X}^0 + \sum_r \sum_j \alpha_j Z_{ri} R_{rj}^0 + \sum_l \sum_j \gamma_j Z_{li} L_{rj}^0 + \beta_E E_i^0 + \beta_p \ln(y_i - p^0) =$$

$$\boldsymbol{\beta}_X \boldsymbol{X}^1 + \sum_r \sum_j \alpha_j Z_{ri} R_{rj}^1 + \sum_l \sum_j \gamma_j Z_{li} L_{rj}^1 + \beta_E E_i^1 + \beta_p \ln(y_i - p^1 - CV)$$

[27] The second Mumbai Urban Transportation Program (MUTPII) will involve resettling 20,000 households located on railway rights-of-way.

where ^{0}'s denote housing and neighborhood attributes originally consumed and ^{1}'s denote attributes consumed with the program. Welfare effects from the relocation program are computed assuming that households pay the same amount for their housing with and without the program. CV should therefore be interpreted as the monetary value of the benefits of the program over and above current housing costs. Welfare effects from the relocation program are computed holding current job location fixed, to capture the short-run effects of the program and replacing current job location by the employment access index, to capture opportunities for workers to change jobs.

Table 10 reports the mean welfare effects of the in situ upgrading program and the relocation program under alternate assumptions about workplace location. The 25th, 50th and 75th percentile of CV values for the households in Table 9 are also presented in the table. The in situ upgrading program is worth, on average, approximately 500 Rs. per month, or about 10% of household income. The range of CV values for the programs reflects the range of incomes of the affected households. The mean benefit of the relocation program differs substantially between households who originally lived in section 79 and those who lived in section 80 and depends crucially on employment and neighborhood effects: Households originally residing in section 80 are, on average, better off under the relocation program than under in situ upgrading; the reverse holds for households from section 79.

To better understand the impacts of relocating, Table 10 presents the mean effects of different components of the slum upgrading program. For example, the mean benefit of the housing improvement associated with the program is 813 Rs. per month for households from section 79 (Distance to work model). Holding workplace location fixed, the mean disbenefit of being moved farther from the workplace is 290 Rs. per month, and the mean disbenefit of changing neighborhood composition 490 Rs. per month.[28] Although the relocation program yields approximately equal housing benefits to both groups, and moves households away from railroad tracks, workers from section 79 are being moved much farther from their jobs than workers who originally lived in section 80. (The latter, on average, actually benefit by being moved closer to their jobs.) The other major difference in welfare between the two groups comes from neighborhood effects. Households who originally lived in section 79, who are primarily Marathi-speaking Hindus, are being moved into a neighborhood with a greater proportion of Muslim and Hindi-speaking households. They lose, on average, from the change in neighborhood composition. For households from section 79, the disbenefits of changes in commute distance and neighborhood composition actually wipe out the housing benefits of the slum improvement program, a result consistent with Lall et al. [16].

The impact of the relocation program however depends on the assumptions made about workplace location. When workplace location is held fixed, the households from section 79, who are on average being moved farther away from their jobs, are worse off than if they are able to change jobs: average welfare losses due to a longer commute go down when distance to work is replaced by the employment accessibility index (job access model). In the particular example illustrated in Table 10, however, the welfare impact of allowing workers to change jobs is not large in quantitative terms. This is because the site of improved housing is not far away from section 79.

Figures 6 and 7 illustrate more clearly the impact of changes in neighborhood composition and employment access on the benefits of slum improvement programs. The figures plot the median CV associated with our sample improvement program, for all

[28] The sum of the mean compensating variations for each component of the program will not add to the mean CV for the program as a whole because the Hicksian bundle enters the utility function non-linearly.

beneficiaries in Table 9, as the location of the improved housing is moved to different places in the city. In Figure 7 we assume that the primary worker in the household maintains his current place of employment when the household relocates; in Figure 6 we measure employment opportunities by the primary worker's employment index. In both figures, lighter areas indicate locations that are welfare-reducing; darker areas indicate moves that are, on average, welfare-enhancing. (In both figures, neighborhood composition changes ipso facto with location.)

When each worker's job location is held fixed (Figure 7), the set of locations for the program that yield positive benefits (positive mean CV) is small indeed. This has two important implications. It suggests that, in the short run, the net benefits of involuntary resettlement programs—even those that improve housing quality—could well be negative and might need to be accompanied by cash transfers if they are not to reduce welfare. The second implication is that if potential participants in voluntary slum relocation programs look only at these programs from a short-run perspective (i.e., assuming that they cannot or will not change jobs), participation is likely to be low.

The set of locations yielding positive benefits is much larger in Figure 6, in which household utility depends on the employment access index. A word of caution is, however, in order. The employment access index does not capture spatial variation in wages, only variation in proximity of jobs. The welfare measures in Figure 6 thus assume that earnings do not vary spatially. To account for spatial variation in wages we estimated hedonic wage equations for the five occupational groups for which the employment access index is computed. The average monthly wage for an unskilled male worker, who is married, 36 years old, has a high school degree is approximately 3600 Rs. in zone 5. It is significantly lower than this only in zone 3, where it is 3000 Rs. per month. This suggests that the welfare gains from a program relocating households to sections 40-57 are likely overstated. The general point made by comparing Figures 6 and 7 is, however, clear: if workers can change jobs, the welfare improvements of relocation programs are greater, and the set of welfare-enhancing sites increases.

VI. Conclusions

In order to design successful slum improvement programs, it is important to determine whether program benefits exceed program costs. It is also important, from the perspective of cost recovery, to determine household willingness to pay for specific program options. The early literature (Mayo and Gross [19]) focused on estimating the percent of income households were willing to spend on housing. This was followed by a literature that attempted to measure, using hedonic price functions, the market value of various improvements, including tenure security and infrastructure services (Crane et al. [10]; Jimenez [13]). It is, however, difficult using the hedonic approach to value attributes that vary by household, such as distance to work, or the percent of neighbors similar to oneself. We believe that both sets of attributes are important in valuing slum improvement programs and have attempted to extend the literature by illustrating the value placed on these amenities by households in Mumbai.

We believe that the model estimated in this paper can be of use in calculating the relative welfare gains from alternative slum improvement programs.[29] It is also useful in predicting which households would be likely to participate in various programs, given costs of participation. In assessing the limited success of sites-and-services programs, Mayo and Gross [19] cite the failure of many programs to choose the right package of services to promote cost-recovery, a result echoed by Buckley and Kalarickal [10].

[29]Unfortunately, comparing benefits with program costs is outside the scope of this paper.

Location is an important component of the design of a slum improvement program. One contribution of this paper is to quantify, for the case of Mumbai, the quantitative importance of location versus other program characteristics. Another is to reinforce the results of other authors (Lall et al. [16]) who suggest that in situ improvements are, in many cases, likely to dominate programs to relocate slum dwellers.

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Table 1. Selected Household Characteristics in Mumbai, by Income Group

	Income Group (in rupees per month)					
Characteristic	< 5 k	5–7.5k	7.5–10k	10–20 k	>20 k	All HHs
Household size (mean)	4	4.4	4.6	4.6	4.4	4.4
Age of Head (mean)	38.2	39.4	41.1	42.9	45	40.4
Female Head (%)	8.8	3	3.9	3.2	1.3	4.5
Education (%)						
Primary or less	20.6	10.8	7.2	2.0	0.3	10.4
College or above	4.0	7.9	17.0	39.2	66.5	18.0
Occupation (%)						
Unskilled	33.9	21.0	11.1	3.5	1.3	17.9
Housing Category (%)						
Squatter settlement	52.2	45.3	34.3	16.1	6.2	37.2
Chawls	37.5	37.5	41.5	27.6	9.9	34.9
Cooperative Housing	5.2	9.6	17.1	47.6	78	21
Other	5.1	7.7	7.2	8.8	5.9	7.1
Housing Tenure (%)						
Less than 5 years	18.6	14.5	13.2	20.1	17.4	16.4
6-9 years	8.2	7.5	7.1	8.5	10.8	8
More than 10 years	34.5	35.3	34.7	31.3	46.6	35
Since birth	38.7	42.7	45	40.1	25.3	40.6
Within-household access to (%):						
Piped Water	48	64	75	92	99	69
Toilet	12	18	31	64	89	32
Kitchen	29	43	61	87	98	54

Table 2. Characteristics of Slum Households

	%
Income Category	
<5k	36.9
5k-7.5k	34.4
7.5k-10k	20.2
10k-20k	7.6
>20k	0.9
Main Earner's Occupation	
Unskilled worker	25.7
Skilled worker	34.2
Petty trader	7.7
Shop owner	8.9
Businessman with no employees	3.0
Businessman with 1-9 employees	1.5
Businessman with 10+ employees	0.2
Self employed professional	0.4
Clerical/Salesman	11.3
Supervisor	2.5
Officer/Junior executive	1.4
Officer/Middle/Senior executive	0.8
Housewife	0.3
Not working	1.7
Other	0.5
Main Earner's Education	
<Primary	8.1
Primary	6.9
Middle school	31.9
High school	36.4
12th grade/Technical training	10.7
College	5.0
Post graduate	1.0
Female Headed Households	5.0

Table 3. Percent of Households in Different Types of Housing by Zone

	Zone						
	1	2	3	4	5	6	Average
Slum	19.2	36.8	35.1	16.9	78.9	47.3	38.7
Chawl/Wadi	52.0	39.9	37.5	50.2	7.3	24.0	35.2
Coop/Employer-Provided Housing	28.7	23.3	27.4	32.9	13.8	28.7	26.1

Table 4. Housing Characteristics by Housing Type

	Slum	Chawl	Coop/ Employer Provided	All Types
Kitchen in the unit	37%	45%	92%	54%
Toilet in the unit	5%	21%	86%	32%
Bathroom in the unit	39%	60%	95%	61%
Water in the unit	50%	69%	98%	69%
Size (sqft)	172	226	428	258

Table 5. Percentage Distribution of Workers Across Job Locations, by Zone of Residence

	Work location								
Home	At home	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6	Outside of GMR	Not fixed
Zone 1	8.5	76.0	5.4	4.1	0.9	1.1	2.9	1.2	0.1
Zone 2	6.2	20.3	60.4	6.1	1.6	1.5	1.0	2.8	0.0
Zone 3	5.0	6.7	5.0	73.1	4.2	2.0	0.7	0.3	3.0
Zone 4	8.8	10.2	4.3	21.2	47.8	0.5	0.8	3.1	3.2
Zone 5	2.1	9.0	7.8	6.7	0.9	54.6	6.7	4.7	7.7
Zone 6	4.4	13.3	8.1	7.7	15.1	3.6	37.6	5.4	4.9
Average	5.8	19.5	15.1	22.3	13.4	9.3	8.5	2.9	3.2

Table 6. Mean Commute Distance by Zone and Income (km)

Zone	<5k	5k-7.5k	7.5k-10k	10k-20k	>20k	All HHs
1	2.3	2.7	3.5	3.7	4.6	3.3
2	2.8	3.5	4.4	4.5	5.7	4.0
3	2.8	3.5	4.7	5.1	5.0	4.1
4	4.8	6.7	6.3	9.5	11.3	7.1
5	3.7	4.5	5.8	4.5	6.0	4.6
6	6.2	7.7	8.8	8.9	10.4	8.0
Average	3.9	4.9	5.7	6.1	7.7	5.3

Table 7. Summary Statistics of Variables in Location Choice Model

	Mean	Sd. Dev	Distribution in population
Slum	0.39	-	
Coop	0.22	-	
Flat	0.20	-	
Good floor	0.81	-	
Good roof	0.42	-	
House size (sqft)	252	174	
Kitchen in house	0.53	-	
Toilet in house	0.30	-	
Bathroom in house	0.61	-	
Water in house	0.69	-	
<300m to rail track	0.20	-	
Zone2	0.17	-	
Zone3	0.24	-	
Zone4	0.23	-	
Zone5	0.13	-	
Zone6	0.12	-	
Neighbor with same religion*			
Hindu	79%	0.15	74%
Muslim	34%	0.19	17%
Christian	8%	0.07	4%
Sikh	4%	0.03	0%
Buddhist	10%	0.06	3%
Jain	4%	0.03	1%
Neighbor with same language			
Marathi	55%	0.17	48%
Hindi	33%	0.17	24%
Konkani	4%	0.04	2%
Gujarati	26%	0.14	12%
Marwari	5%	0.05	2%
Punjabi	4%	0.04	1%
Sindhi	4%	0.06	0%
Kannada	2%	0.02	1%
Tamil	4%	0.04	2%
Telugu	5%	0.07	1%
English	7%	0.06	1%
1st earner commute distance (km)	5.5	7.3	
Job access index for main eaner	2.39	1.16	
Hicksian bundle (Rs. /month)	8275	7217	

*First column: For Hindu households in the sample, the average % of Hindus in the neighborhood

Table 8. Estimation Results for Model of Location Choice

First Stage Coefficients	Model 1	Model 2
ln(Hicksian bundle)	5.12	5.06
	[54.33]**	[54.61]**
Main earner commute***	-0.27	-0.23
	[72.30]**	[14.43]**
Same religion(<1%)	65.62	81.41
	[2.71]**	[3.45]**
Same religion(1-5%)	20.07	19.60
	[3.03]**	[3.08]**
Same religion(5-10%)	14.59	15.01
	[3.99]**	[4.24]**
Same religion(10-25%)	1.05	1.82
	[1.16]	[2.08]*
Same religion(25-50%)	3.11	3.03
	[6.79]**	[6.91]**
Same religion(50-75%)	1.03	1.13
	[3.31]**	[3.74]**
Same religion(>75%)	3.46	2.53
	[11.10]**	[9.02]**
Same language(<1%)	102.62	102.19
	[6.38]**	[6.54]**
Same language(1-5%)	11.07	15.31
	[2.29]*	[3.29]**
Same language(5-10%)	13.25	12.02
	[4.35]**	[4.07]**
Same language(10-25%)	4.31	5.14
	[6.40]**	[7.94]**
Same language(25-50%)	2.29	2.39
	[7.84]**	[8.43]**
Same language(50-75%)	1.24	1.06
	[3.99]**	[3.55]**
Same language(>75%)	-1.08	-0.11
	[1.31]	[0.13]
Constant	-1.09	0.31
	[23.06]**	[7.02]**
Observations	4023	4023
Pseudo R-squared (1st stage)	0.39	0.24
LL	-13787	-16225
Second Stage Coefficients		
1st PC for house characteristics	0.50	0.49
	[69.24]**	[71.12]**
2nd PC for house characteristics	-0.17	-0.17
	[11.46]**	[12.09]**
zone==2	0.19	-0.37
	[3.22]**	[6.51]**
zone==3	1.23	-0.30
	[21.99]**	[5.68]**
zone==4	1.90	-0.50
	[33.82]**	[9.48]**
zone==5	0.97	-0.41
	[15.15]**	[6.85]**
zone==6	1.74	-0.10
	[26.77]**	[1.61]
Within 0.3km from rail track	-0.05	-0.06
	[1.37]	[1.70]
R-squared (2nd stage)	0.65	0.59

Implied coefficients on original variables:

	Model 1	Model 2
Slum	-0.34	-0.33
	[53.00]**	[54.68]**
Coop	0.58	0.56
	[43.99]**	[45.46]**
Flat	0.60	0.59
	[40.74]**	[42.14]**
Good floor	-0.05	-0.06
	[2.12]**	[2.50]**
Good roof	0.39	0.38
	[53.09]**	[54.77]**
Size	0.28	0.27
	[53.65]**	[54.94]**
Kitchen	0.20	0.19
	[18.83]**	[19.04]**
Toilet	0.48	0.46
	[57.78]**	[59.57]**
Bathroom	0.21	0.20
	[19.73]**	[19.97]**
Water	0.20	0.19
	[22.47]**	[22.79]**

WTP (at HH Income of Rs.6250 /month)

	Model 1	Model 2
Main earner commute	-329	-283
Same religion(<1%)	801	1006
Same religion(1-5%)	245	242
Same religion(5-10%)	178	185
Same religion(10-25%)	13	22
Same religion(25-50%)	38	37
Same religion(50-75%)	13	14
Same religion(>75%)	42	31
Same language(<1%)	1252	1262
Same language(1-5%)	135	189
Same language(5-10%)	162	148
Same language(10-25%)	53	63
Same language(25-50%)	28	30
Same language(50-75%)	15	13
Same language(>75%)	-13	-1
Slum	-411	-405
Coop	704	696
Flat	734	726
Good floor	-62	-70
Good roof	480	473
Size (at 200sqft)	1.7	1.7
Kitchen	243	235
Toilet	581	572
Bathroom	252	244
Water	246	239

* significant at 5%; ** significant at 1%

*** In the first column distance to current job and in the second column, average distance to nearest 100 jobs within main earner' occupation category

Table 9. Summary Statistics of Households in Targeted Area

	Current situation		Upgrading	
	Section 79	Section 80	Relocation	In-situ Improvement
# in sample	80	42		
Hicksian bundle (Rs. /month)	5009	5993	Unchanged	Unchanged
Flat	0.00	0.00	NO	Unchanged
Good floor	0.75	0.45	YES	Unchanged
Good roof	0.05	0.00	YES	YES
House size (sqft)	141	162	165	Unchanged
Kitchen	0.21	0.26	NO	Unchanged
Toilet	0.00	0.00	NO	Unchanged
Bathroom	0.10	0.07	NO	Unchanged
Water	0.26	0.24	YES	YES
1st earner commute distance (km)	5.0	4.9	5.7	Unchanged
1st earner Job Access index	1.6	2.6	2.0	Unchanged
<300m to rail track	0.58	0.40	NO	Unchanged
Neighbor with same religion				
Hindu	73%	61%	45%	Unchanged
Muslim	15%	31%	45%	Unchanged
Christian	NA	NA	1%	Unchanged
Sikh	NA	NA	0%	Unchanged
Buddhist	17%	12%	8%	Unchanged
Jain	NA	NA	0%	Unchanged
Neighbor with same language				
Marathi	61%	40%	34%	Unchanged
Hindi	19%	47%	60%	Unchanged
Konkani	1%	NA	0%	Unchanged
Gujarati	1%	NA	0%	Unchanged
Marwari	13%	NA	0%	Unchanged
Punjabi	NA	NA	0%	Unchanged
Sindhi	NA	NA	0%	Unchanged
Kannada	0%	1%	0%	Unchanged
Tamil	8%	NA	0%	Unchanged
Telugu	NA	NA	1%	Unchanged
English	NA	NA	1%	Unchanged

Table 10. Effects of Slum Upgrading Programs

	Relocation Case (Dist to work model)		Relocation Case (Job access model)		In-situ Improvements	
Section	79	80	79	80	79	80
Total Compensating Variation (Rs. /month)						
Mean	-89	1194	216	1315	474	591
Std Dev	1373	1595	1289	1697	326	377
25%	355	1369	587	1581	672	672
50%	-107	731	73	929	269	630
75%	-646	394	-463	371	269	269
Mean contribution*						
House	813	911	800	889		
Commute	-290	87	-119	169		
Rail track	29	24	34	29		
Neighbor	-490	416	-366	518		

* The sum of the mean compensating variations for each component of the program donot add to the mean CV for the program as a whole because the Hicksian bundle enters the utility function non-linearly.

Figure 1. Map of Zones in Mumbai

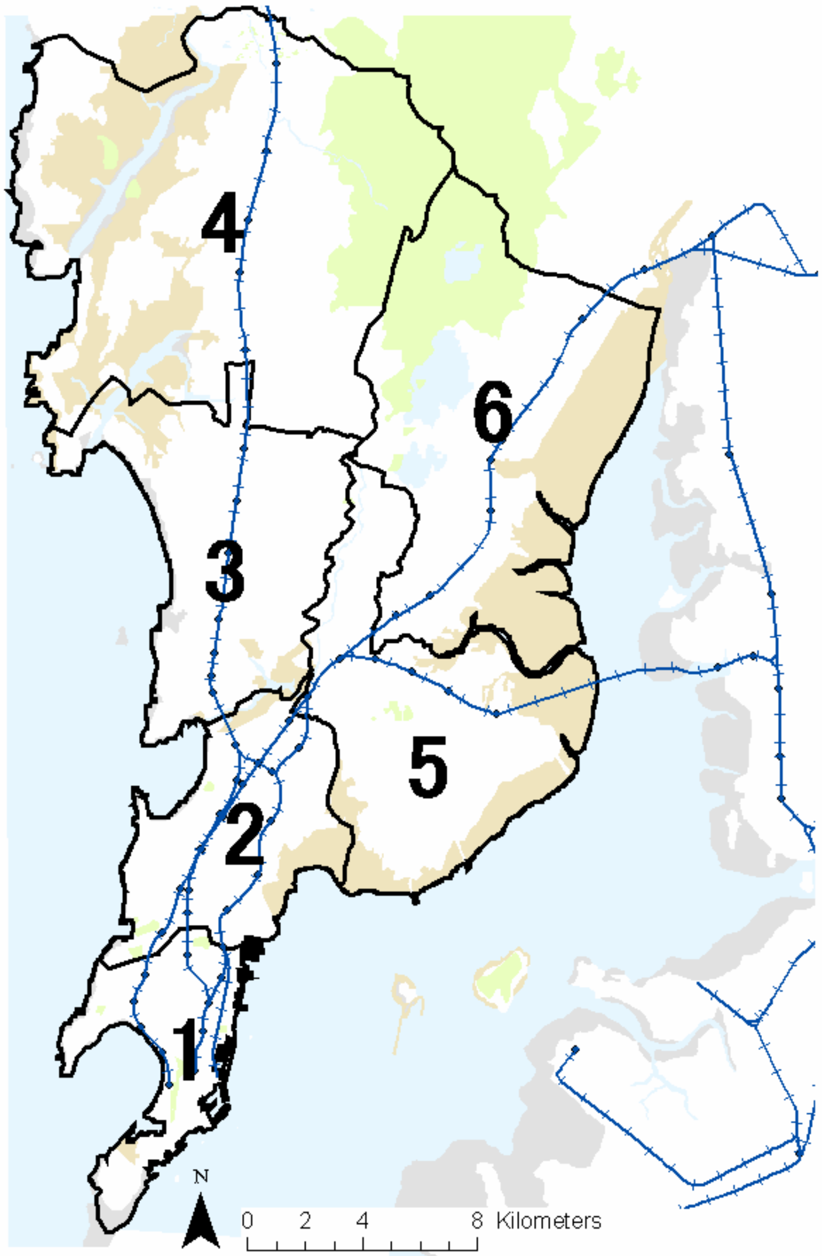

Figure 2. Location of Slum Households

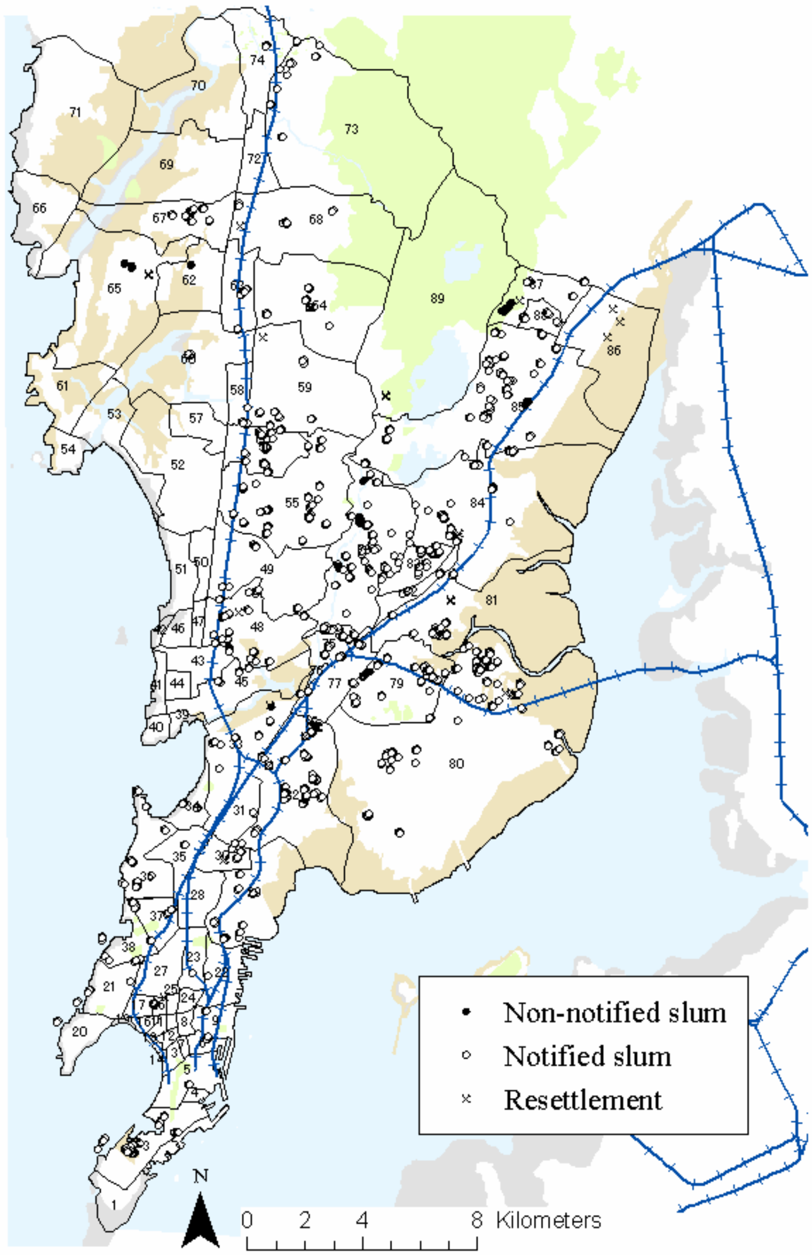

Figure 3. Location of Non-slum Households

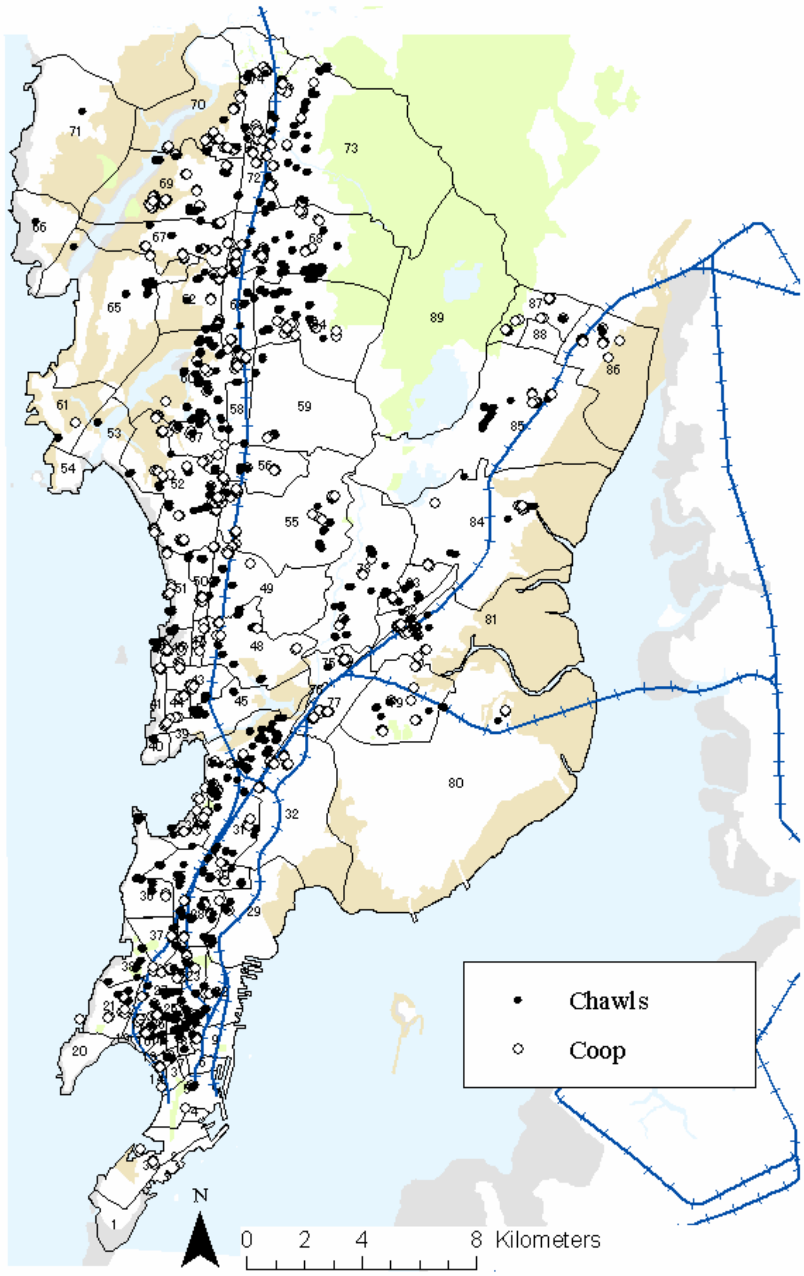

Figure 4. Sample Distribution for One-way Commute Distance

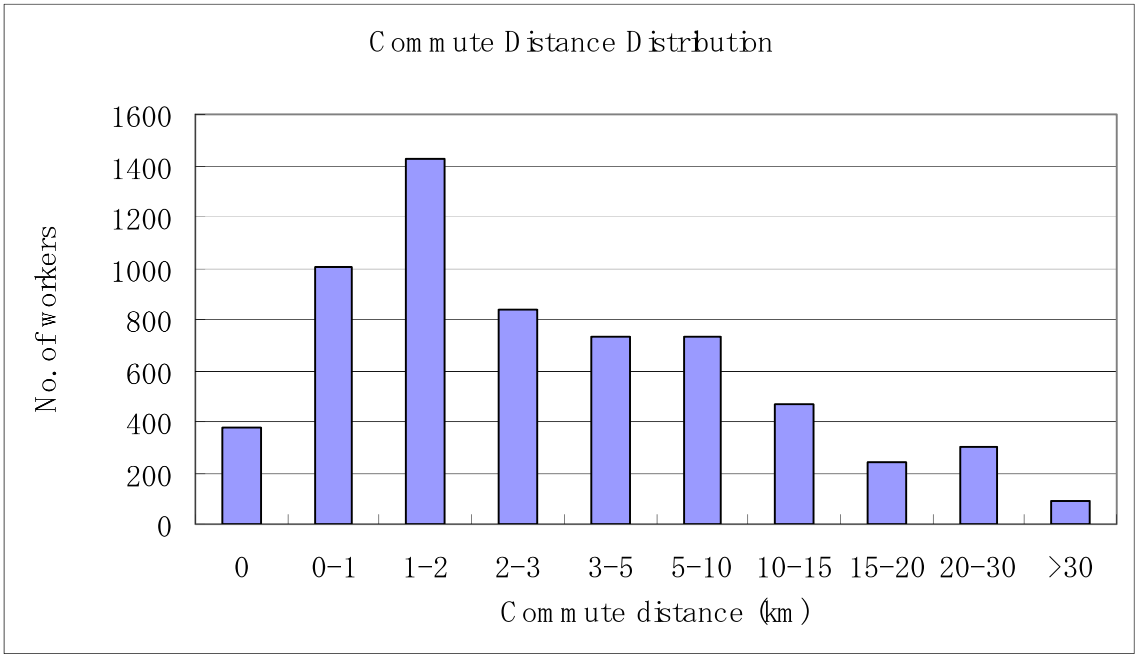

Figure 5. Target Households and Relocation Site of the Slum Upgrading Program

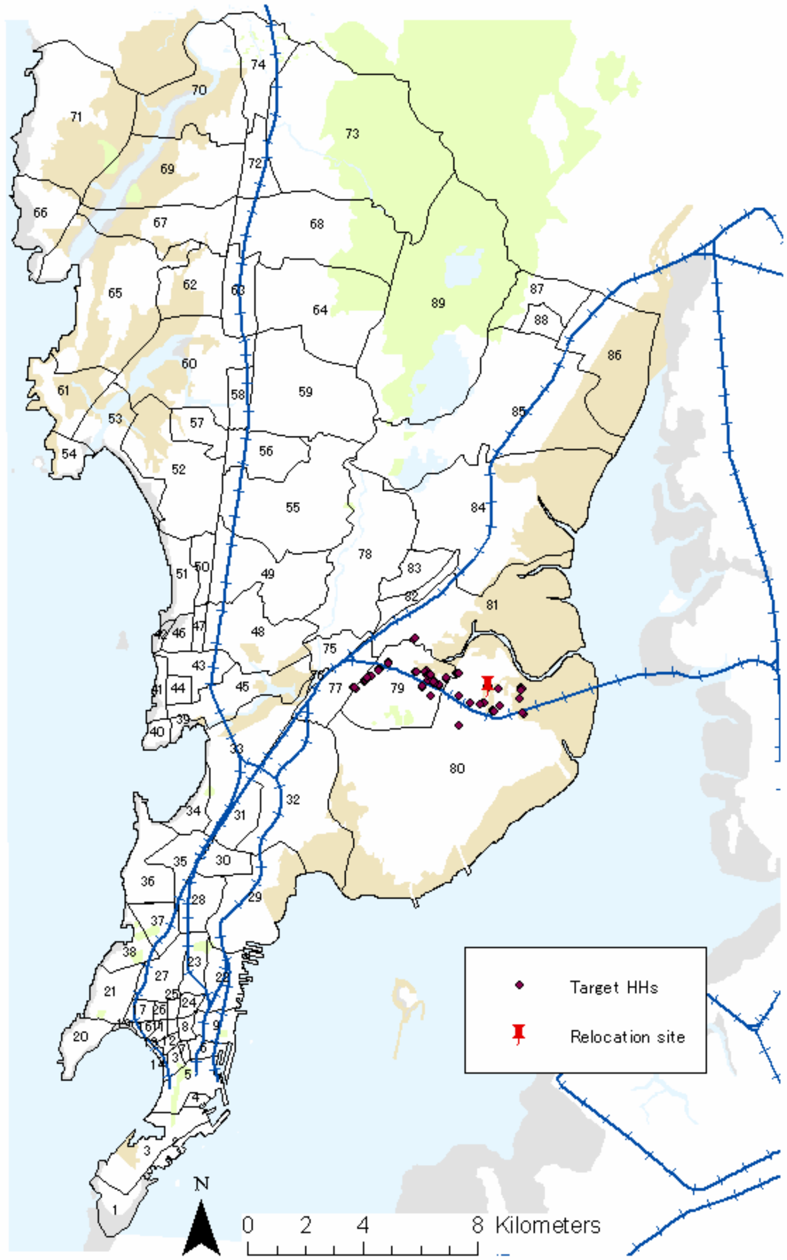

Figure 6. CV for the Relocation Program Using Job Access Model

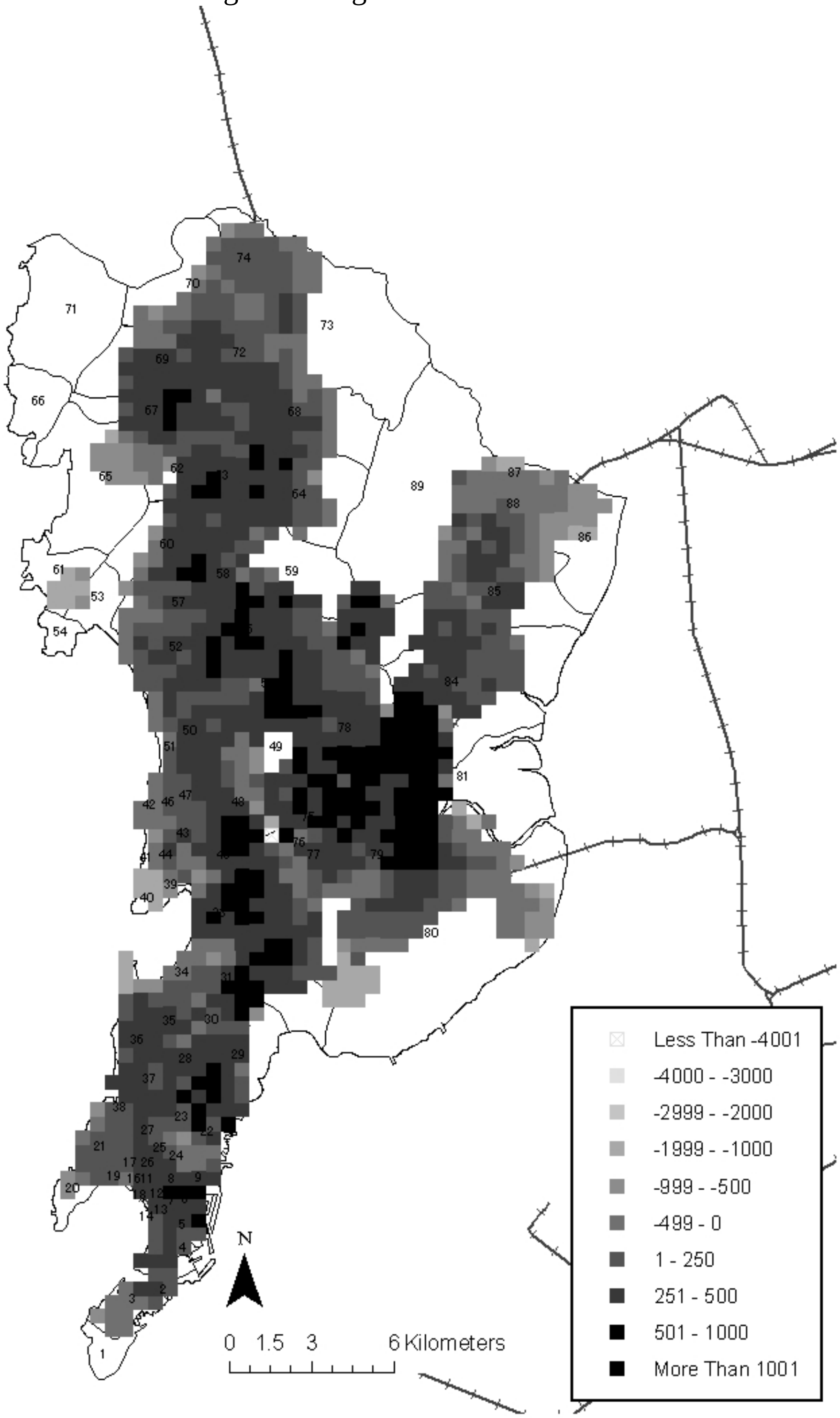

Figure 7 CV for the Relocation Program Using Distance to Work Model

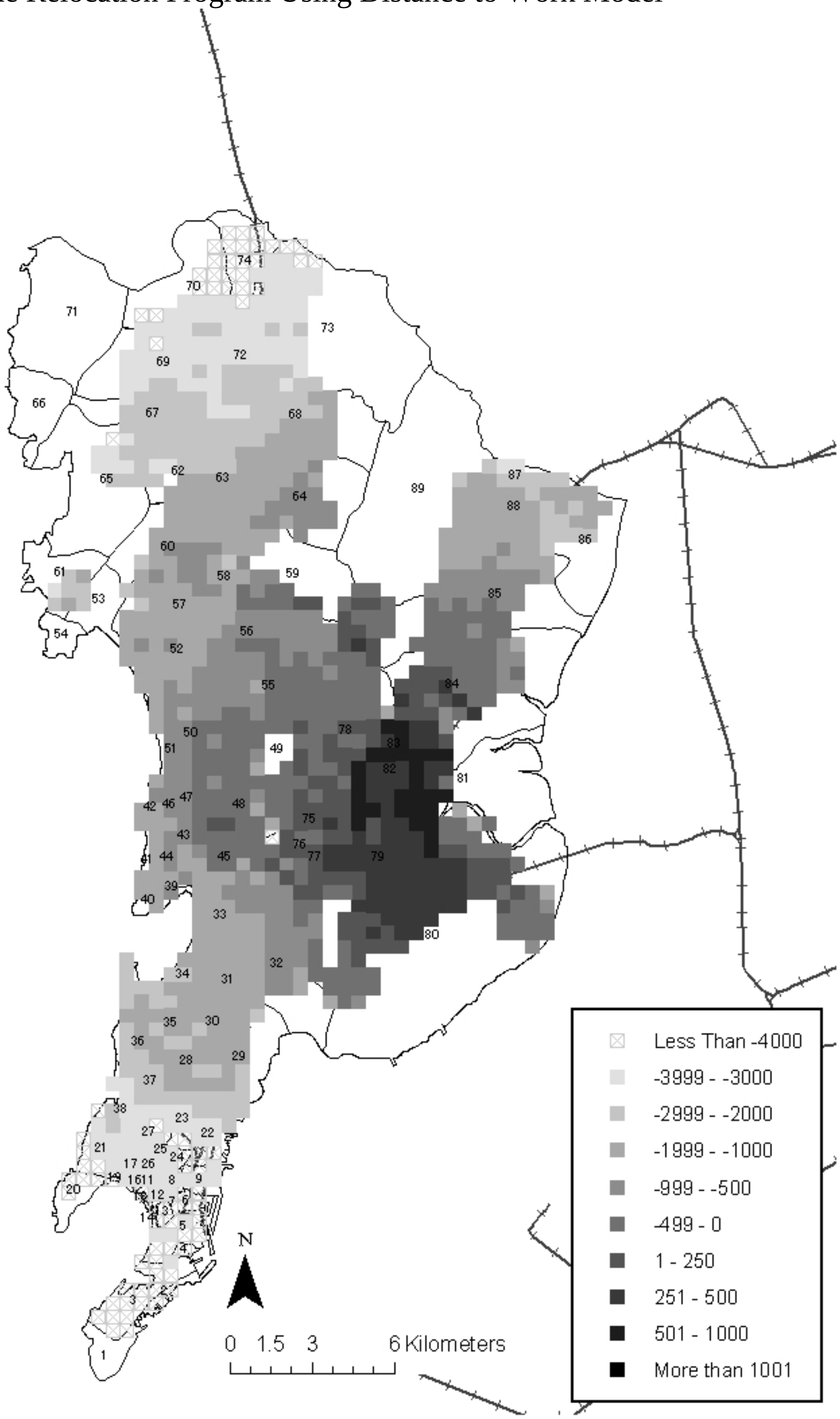

Table A1 Hedonic Rent Function Estimates

Dependent var=ln(rent)	1	2
Slum	-0.09	-0.09
	[4.34]***	[4.36]***
Coop	0.29	0.28
	[7.88]***	[7.78]***
flat	0.34	0.34
	[9.28]***	[9.33]***
Good floor	0.06	0.06
	[2.55]**	[2.63]***
Good wall	0.35	0.36
	[8.39]***	[8.44]***
Good roof	0.08	0.08
	[3.56]***	[3.33]***
Size	0.40	0.40
	[20.10]***	[20.18]***
Kitchen	0.06	0.07
	[2.91]***	[3.29]***
Toilet	0.10	0.10
	[3.80]***	[3.47]***
Bathroom	0.07	0.07
	[3.19]***	[3.16]***
Water	0.05	0.04
	[2.56]**	[2.11]**
Near rail track	-0.02	-0.03
	[1.22]	[1.45]
zone==2	-0.07	-0.08
	[1.60]	[1.78]*
zone==3	-0.13	-0.13
	[2.02]**	[2.07]**
zone==4	-0.22	-0.22
	[2.79]***	[2.80]***
zone==5	-0.20	-0.20
	[3.26]***	[3.22]***
zone==6	-0.25	-0.25
	[3.42]***	[3.41]***
Neighbor's income	0.00004	0.00004
	[11.12]***	[10.88]***
Ln(distnace to CBD)	-0.09	-0.09
	[2.83]***	[2.66]***
Near rail station		0.00
		[0.10]
Near bus stop		0.14
		[4.86]***
Vehicle accessible road		0.04
		[1.80]*
Constant	4.56	4.38
	[38.46]***	[35.53]***
Observations	4132	4132
Adjusted R-squared	0.639	0.641

Absolute value of t statistics in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

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