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ABSTRACT

Municipal solid waste management is a challenging issue in developing countries. An unclean neighborhood could have a significant negative impact on housing property values too as it may lead to numerous diseases in addition to diminished aesthetic value. This study examines the effects of municipal solid waste collection services at the neighborhood level on housing property values using the hedonic price model. We use a sub-sample of nationally representative household survey data from urban areas as well as primary data collected from one of the metropolitan cities in Nepal. Our results suggest that city residents place a high price premium (between 25% and 57%) on cleaner neighborhoods and less (−11%) on open drains. These numbers indicate that better waste management will bring high returns to home owners, and also the municipality in cities where the tax base includes the assessed value of property.

1. Introduction

The urban population has seen a rapid increase globally, especially in low and middle-income countries. Currently, it accounts for 55% of the world's population and is expected to increase to 68% by 2050 (United Nations, 2018). Economists and urban planners are nearly unanimous that urbanization promotes economic growth and improves living standards of urban dwellers (Chen, Zhang, Liu, & Zhang, 2014). However, urbanization brings with it its own challenges among which are an increase in impervious areas due to concretization in built-up areas leading to increased run-off, water logging and flooding during heavy rainfall events (Pervin et al., 2020) and an increase in the volume of solid waste with population growth (Jha et al., 2008), particularly, plastic waste (Bhardwaj, Baland, & Nepal, 2020).

In developing countries, the municipal solid waste (MSW) issue has become a major threat to sustainable development (Thi, Kumar, & Lin, 2015). The lack of clear rules coupled with the poor institutional capacity of municipalities to enforce existing rules and regulations for managing solid waste; inadequate infrastructure for collection, transportation, treatment and disposal of MSW; insufficient resources; inadequate technical expertise and low public awareness levels have made the municipal solid waste management difficult (Hazra & Goel, 2009; Hui & Li'ao, W., Fenwei, S., & Gang, H., 2006; Marshall & Farahbakhsh, 2013; Rai, Bhattarai, & Neupane, 2019a). The lack of proper management results in the scattering of waste in urban centers and on roadsides and drainage as well as haphazard dumping, which has increased the risk of exposure not only to environmental and health-related problems (Srivastava, Ismail, Singh, & Singh, 2015) but also to urban flooding and water logging (Pervin et al., 2020). On the other hand, solid waste management is one of the costlier activities of the local authorities. In the absence of at-source segregation, the volume of MSW is unnecessarily high, requiring more landfill space. Existing evidence suggests that proper solid waste management may require up to half of the total municipal budget in some developing countries (Henry, Yongsheng, & Jun, 2006).

Considering the extent to which waste management remains an unresolved problem in cities of developing countries, a question may be asked why people prefer to live in the comparatively polluted cities instead of the cleaner environs of the villages. The answer might be economic opportunities which, for urban migrants in developing countries, outweigh environmental aspects as per the environmental Kuznets curve hypothesis (Kuznets, 1955). However, it is also a fact that cities do not offer a similar environment for all its residents depending on location. Therefore, it would be pertinent to assess the value that urban residents put

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on a cleaner neighborhood. City residents will have their own list of preferred indicators or attributes including a cleaner neighborhood when selecting the location (Law, 2017). Among other things, urban residents' preferences for a given location could be reflected in housing property values so that houses with exactly the same structural characteristics would carry different prices in different neighborhoods depending on the attributes of the neighborhoods and associated preferences of residents (Law, 2017).

Literature on the spatial hedonic housing price model suggests that, besides structural characteristics, environmental factors also influence property prices. While beaches, scenic views and types of forest management in the case of rural areas (Nepal, Karki Nepal, & Berrens, 2017) are some of the environmental amenities influencing property prices, among dis-amenities can be listed hazardous waste sites (Boxall, Chan, & McMillan, 2005; Kohlhase, 1991; Michaels & Smith, 1990; Rivas Casado, Serafini, Glen, & Angus, 2017), landfill sites (Hite, Chern, Hitzhusen, & Randall, 2001; Nelson, Genereux, & Genereux, 1992), open drainage (Irfan, 2017), airports and highways (Day, Bateman, & Lake, 2007; Nelson, 2004; Van Praag & Baarsma, 2005), air pollution (Neill, Hassenzahl, & Assane, 2007; Smith & Huang, 1995), water quality (Cho, Roberts, & Kim, 2011; Leggett & Bockstael, 2000), and flood risk (Bin & Polasky, 2004; Daniel, Florax, & Rietveld, 2009; Rabassa & Zoloa, 2016).

An unclean neighborhood, due to problems with solid waste management, could exert a similar negative impact on housing prices in developing countries. However, there is a gap in the literature on how the presence of solid waste management services, as a proxy for clean neighborhoods, might affect property prices. Our study addresses the gap by assessing the effects of solid waste collection services on housing property values. It will contribute towards efforts to sensitize urban residents, municipal authorities and policy makers in Nepal as well as other developing countries facing similar situations to make municipal solid waste management a part of the urban culture. This is especially important when, as in the case of Nepal, the country is converting small towns into municipalities in order to provide better services to urban residents. Our results suggest that city residents place a substantial price premium (25–57%) on housing units that are located in cleaner neighborhoods.

2. Materials and methods

2.1. Basic theory

The utility or satisfaction that consumers obtain from housing units is based on several factors, among them, structural characteristics of the housing unit such as plot size, floor area, number of rooms, bathrooms, wall and roof materials; neighborhood characteristics such as proximity to market center, banks, schools, hospitals and police stations as well as crime rates in the community; and environmental characteristics such as the presence of public parks, pollution levels, and waste management services. The price of a residential unit in a given location depends on all these attributes or characteristics. Thus, when a consumer buys a housing unit, the consumer essentially pays not only for the housing unit but also for the local environment and community characteristics. But these characteristics are not separately priced and buyers would not know the price they pay for the different attributes of a housing unit as the housing unit comes as a composite commodity with a bundle of attributes. The hedonic price theory helps us to disentangle the associated values of these attributes to the residents, often called the implicit prices of the attributes of housing units, in order to make informed decisions (Rosen, 1974).

Formally, a representative consumer i with characteristics ω_i, maximizes utility $U_i = U(X, H; \omega_i)$ from consuming a housing unit (H) and all other goods and services (X). The consumer takes the prices of all goods and services as given including the price of a housing unit, $P(H)$ and chooses a housing unit in a preferred location, given the income (Y) of the consumer. For simplicity, we normalize the price of X to 1 without loss of generality. Therefore, the consumer faces a budget constraint: $Y_i = X_i + P(H_i)$. While choosing a housing unit, the consumer actually chooses the attributes of the house ($H = H(h_i, h_2, \ldots\ldots, h_n)$), its locational characteristics, and neighborhood characteristics. Optimization requires $\frac{\partial U/\partial h_i}{\partial U/\partial X} = \frac{\partial P}{\partial h_i}$, which gives the demand for the housing unit that depends on the environmental quality associated with its location, Q, neighborhood attributes in the vicinity, N, and importantly the set of structural characteristics, H, of the housing unit (Baumont, 2009).

In such a situation, the corresponding hedonic price model defines the functional relationship between housing price P and other variables: structural (H), environmental (Q) and neighborhood (N) characteristics as in Eq. (1):

$$P = f(H_i, N_i, Q_i) \tag{1}$$

The marginal implicit price expressed in Eq. (2) of the k^{th} externality (i.e., environmental characteristics), say Q_k, can be assessed from the first derivative of the Eq. (1) with respect to the housing attribute, k. Eq. (1) can be estimated using the regression analysis with housing price as a dependent variable and all of the characteristics as explanatory variables (Freeman, Herriges, & Kling, 2014). The partial derivative of Eq. (1) provides the marginal implicit price, also called the marginal willingness to pay (MWTP) for the cleaner environment, as expressed in Eq. (2):

$$(MWTP)_k^Q = \partial P / \partial Q_k \tag{2}$$

Eq. (2) provides the marginal implicit price of the cleaner environment with the provision of municipal solid waste collection. As the first stage model does not provide the demand for the solid waste collection service (Mei, Hite, & Sohngen, 2017), the hedonic price theory recommends the second stage analysis in order to estimate the demand for solid waste collection services or environmental quality (Mei et al., 2017; Netusil, Chattopadhyay, & Kovacs, 2010; Rosen, 1974). Since our objective is to understand the value of the cleaner neighborhood, the first stage implicit price of the waste collection service is deemed sufficient for our purposes.

The two-step process also requires data from several markets for proper identification since the marginal implicit price from Eq. (2) is constant for a given market if Eq. (1) is estimated as a linear equation (Mei et al., 2017). However, there is an issue of simultaneity where both price and quantity are determined at the same time (Diamond & Smith, 1985). As our data does not allow dividing the markets into several segments due to the small sample size (discussed in the data section), we limit our analysis to the first stage.

As the hedonic price model is applicable in a single housing market, we divided our study area, i.e., the urban centers of Nepal, into two parts: the hills and the *terai*. The two markets are geographically separate and different in the sense that the *terai* is the flat land in the southern part of the country while the hilly area lies at a higher elevation. The culture, ethnic composition and traditions are also different between the two geographic regions as is the housing market.

Various models, including linear, Box-Cox, semi-logarithmic, and double logarithmic, have been used in hedonic studies (Mei, Hite, & Sohngen, 2017; Nepal, Karki Nepal, & Berrens, 2017; Netusil, Chattopadhyay, & Kovacs, 2010). Some literature favors the use of the linear and Box-Cox models that produce the smallest mean on the related attributes (Cropper, Deck, & McConnell, 1988). However, there is an increased risk of random errors in complex data transformation for missing observations. While these methods can accurately estimate the marginal willingness-to-pay (MWTP) for attributes, they could lead to biased estimations (Kuminoff, Parmeter, & Pope, 2010). For this reason, a change in variable dynamics and the fixed effect Box-Cox conversion is worthy of attention. The semi-log model may minimize possible errors and bring flexibility (Malpezzi, 2003). Thus, in this analysis, taking the cue from the literature, we use log transformation for continuous variables including housing price, floor area, distance to some of the community attributes, and level for count or binary variables (Nepal, Karki Nepal, & Berrens, 2017). Log transformation also helps to address the heteroscedasticity or the scale issue. Our empirical model is thus:

$$LnP_{ind} = \alpha + \beta_1 H_{ind} + \beta_2 N_{nd} + \beta_3 Q_{nd} + \delta_d + \varepsilon_{ind} \tag{3}$$

where, P_i is the price of house i, H_i is a vector of structural characteristics of house i (plot size, number of rooms, age of the house, wall materials, etc.), N_n is a vector of neighborhood characteristics of community n (proximity to hospital, market, school, bus-stop, highway, and police post), Q_n is a vector of environmental attributes (environmental quality, presence of solid waste management services in the community n, proximity to the main river, open drainage, and flood-prone area), δ_d is spatial fixed effects in district d, and ε_{ind} is an error term. The spatial fixed effects are used to account for unobserved heterogeneity or missing characteristics of the spatial units in the data in order to reduce omitted variable bias. The distance to the main river is controlled, when the information is available in the case study, as distance to the river measures the risk of river bank erosion and flooding during monsoon season. As mentioned above, we use log transformation of the continuous variables including the housing price (dependent variable) while no such transformation is used for count and categorical variables when estimating Eq. (3).

As we are using cross-sectional data for estimating Eq. (3) while waste management services may not be introduced at random in urban centers, we rely on a quasi-experimental design to examine the robustness of the estimated hedonic implicit price of environmental quality. We mainly use the propensity score matching (PSM) method (Dehejia & Wahba, 2002; Rosenbaum & Rubin, 1983) as PSM is a non-parametric approach that can be applied in reducing bias where observational data is used for analyzing the impact of certain interventions such as solid waste management in urban areas, a proxy for environmental quality (d'Agostino, 1998). This approach helps in minimizing the selection bias coming from observational data by matching observations between intervention (presence of solid waste management service) and control (absence of solid waste management service) groups using the predicted propensity score (Rosenbaum & Rubin, 1983). The existing literature provides a detailed account of how matching may help eliminate selection bias in a non-experimental setting (Smith & Todd, 2005). Variables used for estimation are defined in Table 1.

2.2. Study area

Nepal has been experiencing rapid urbanization and increasing rural-urban migration after the reinstatement of democracy in the early 1990s (Acharya & Leon-Gonzalez, 2018). The rural population is migrating in increasing numbers towards urban centers for education and economic opportunities. The classification of cities, towns and settlements are also changing in Nepal after the introduction of the new Constitution in 2015. According to the new classification, over 58% of the total Nepali population now lives in municipalities whereas it was around 20% a few years prior to the reclassification. But even if the new classification categorizes small towns and cities as municipalities, not all such new municipalities have urban infrastructure, including planned settlements that provide basic infrastructure such as roads, grid electricity, drainage and other such services including municipal solid waste management and safe drinking water. In Nepal, the population distribution is disproportionately located in limited urban centers. There are, at present, six metropolitan cities in Nepal, two of which are located inside the Kathmandu valley while the other four are located outside of it.

For this study, we only consider urban settlements that had been classified as municipalities prior to the new classification. These 'old' municipalities, which are located across the country, in both the *terai* and the hilly areas, mainly include the district headquarters and a few other urban centers (Fig 1). The *terai*, which is only 20% of the total land area of the country, is home to almost 50% of the total population while only a small fraction of the population lives in the northern part of the country that comprises high altitude mountains with no urban centers. Fig 2 shows the districts across the country with municipalities as their district headquarters. In addition to the entire urban area from both the *terai* (southern belt that borders India) and the hills (north to the *terai* belt, the study includes the Bharatpur Metropolitan City (BMC) as a case study (colored red in Fig 1), with primary data gathered from the 14 wards of the city.

Bharatpur is a fast growing metropolitan city (BMC) in the Chitwan district, which is 20 min away by air and around 4 h of travel (150 km) by road from the capital city of Kathmandu. It is located in the south-central part of Nepal. Bharatpur, which lies on the bank of the Narayani River, is the closest metropolitan city to the capital city of Kathmandu. With a sub-tropical climate, it is also one of the fastest-growing cities in Nepal having been upgraded to the status of a sub-metropolitan city in 2014 and declared a metropolitan city in 2017. BMC is spread over 433 km^2 with a population of over 300,000. Migration to the southern plain, including Bharatpur, began after the eradication of Malaria in the 1960 s (McLean, 1999). Bharatpur, therefore, could be described as a city of migrants. The east–west highway, one of the major highways in Nepal, passes through the heart of the city. It is situated at an altitude of 251 m from the mean sea level with an average annual rainfall of 1,500 mm and an average temperature of 25 °C ranging from 10 °C to 40 °C.

2.3. Data and variables

The data for this study comes from two sources. The first source is the Nepal Living Standards Survey 2010/11 (NLSS III), which is the third wave of a nationally representative household survey. The second source is the primary survey collected by the research team. Each of these data sources is discussed below.

2.3.1. National data

Though somewhat dated, the NLSS III survey is the most recent and publicly available nationally representative survey that provides the needed information to conduct the hedonic analysis of the implicit price of environmental quality in Nepal. The total sample size of the NLSS III was 5988 households. We only consider an urban sub-sample in our analysis since we are using municipal solid waste management services as the key variable of interest. In the survey, only the self-reported housing price is available for the owner-occupied housing units. Our sample, therefore, comprises 1,382 households from 56 urban centers (see Fig 1) that includes 42 districts from both the hills and the *terai* region (see Fig 2) across the country.

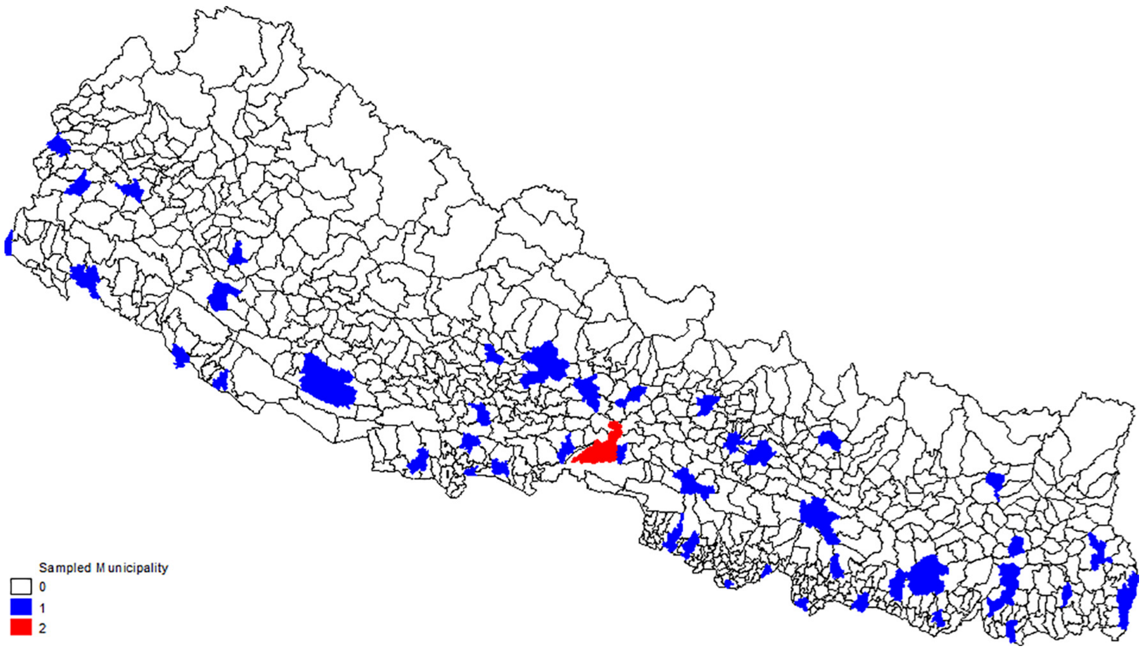


Fig. 1. Sampled municipalities across the country.

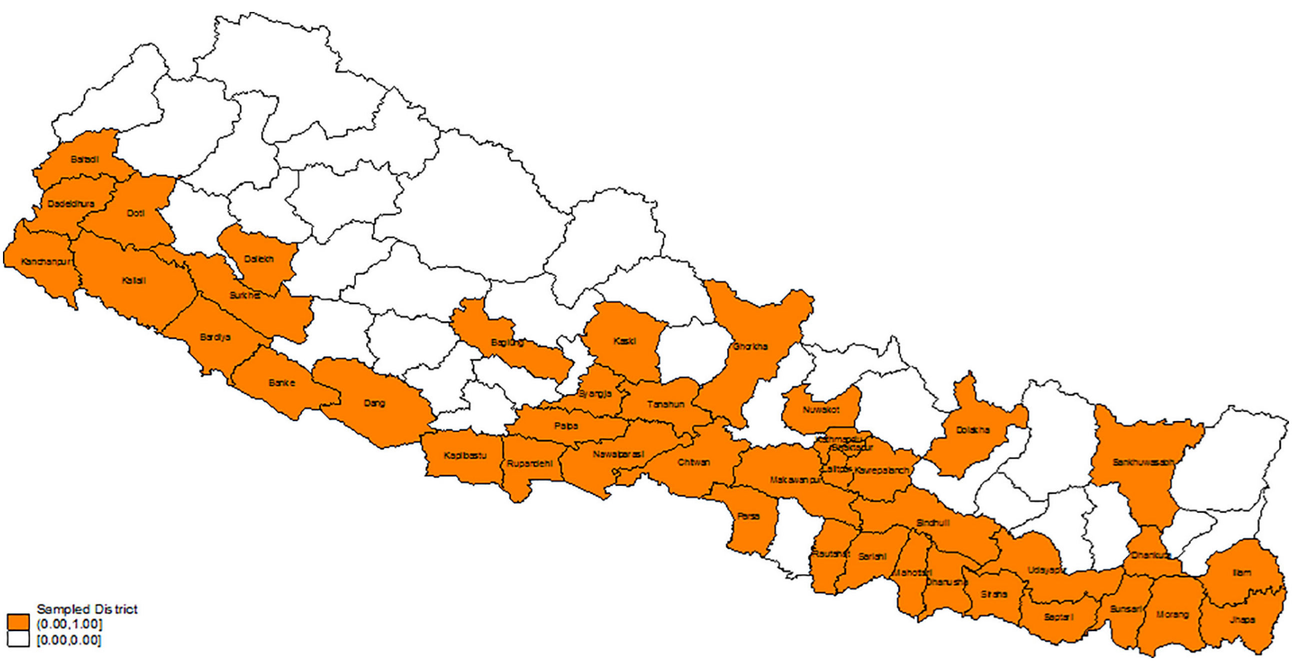


Fig. 2. Sampled districts with municipalities.

Ideally, prices of housing units for hedonic analysis should come from transactions of housing units in the competitive market where the demand price of a housing unit equals the offer price at equilibrium (Rosen, 1974). However, there are a number of issues in collecting and using market transaction data in a low-income country where the housing market is far from competitive (Nepal, Karki Nepal, & Berrens, 2017). As a result, the literature on the hedonic price model is thin when it comes to developing countries. The main problem in using actual market prices is under-reporting of the sales price for various reasons including tax purposes. Although administrative data is available at property registration offices throughout Nepal, this information does not provide the actual value of the housing units due to underreporting of the actual sales price. Even if such data in principle could be collected, structural, community and environmental characteristics of the housing units, which are the key ingredients in undertaking a hedonic price analysis, would not be available in the administrative data. Therefore, we did not collect or use administrative data in our analysis. A developer survey would be an alternative but, in Nepal, there are as yet only a few developers since the profession has only begun to emerge in recent years. Therefore, most of the housing units are built by private individuals who first buy land, and contract labor and purchase necessary materials.

The NLSS III data includes the self-assessed price of residential units, including the structural and community characteristics, which is used in this paper.[1] Similar information has been used in Nepal, Karki Nepal, & Berrens, 2017 for assessing the value of forests under different management regimes. The use of self-reported property prices in hedonic analysis is now well established in the literature (Gonzalez-Navarro & Quintana-Domeque, 2016). Although the literature suggests that self-reported housing prices may be biased, which is true to some extent, the extent of bias is not more than between 3% and 8% (Agarwal, 2007; Gonzalez-Navarro & Quintana-Domeque, 2009, 2016; Goodman & Ittner, 1992; Kiel & Zabel, 1999). Moreover, the extent of bias may depend on the duration of the tenure or age of the house. Therefore, we use the age of the house to account for such potential biases. With regard to environmental quality, our interest is in the provision of solid wastes management services in the community, which is available in the NLSS III data set.

2.3.2. Case study data

For our case study, the study team carried out consultations between July 2016 and March 2017 with stakeholders prior to designing the survey instrument for collecting data. The consultations were to understand past and existing solid waste management activities and issues and areas needing improvement relating to MSW management. The team consulted staff of the metropolitan city, private contractors who collect and dispose MSW, and leaders of selected neighborhoods in the cities, called Tole Lane Organizations (TLOs).

Municipal officials indicated that they lack adequate resources for effective collection of solid waste and that the participation of municipal households was not optimal. Households pay a monthly user fee of NPR 30 to NPR 100 depending on the weekly frequency of the waste collection service in the given TLO. However, private contractors were facing both financial and human resource constraints as the user fee was insufficient to manage the solid waste properly. Moreover, unskilled laborers who were involved in waste collection preferred to work on a part-time basis, which limited the quality of service delivery. Based on these consultations, the team first developed two types of protocols for focus group discussions (FGDs), one each for business and residential areas. A total of six FGDs–two in residential areas and four in business areas–were conduction in April 2017.

Based on the FGDs, two sets of questionnaires (for community and household level) were prepared and pretested in an area which was just outside the study area of the Bharatpur metropolitan city but which had almost identical characteristics. We then randomly selected 150 TLOs out of the total 352 TLOs in the city for our study. The TLOs are smaller communities organized for developing the local community comprising 100 households on average. There are multiple TLOs within each ward with 14 wards in our study area.[2] The number of TLOs, which were selected randomly from each ward, was proportional to the total number within a ward. We selected seven households from each TLO via a systematic random sampling method. We interviewed heads of households of either gender as per their availability. In all, 1,050 households were interviewed.

The survey collected housing characteristics and self-reported prices of the housing units as property transaction data was not available (as mentioned above when discussing national survey data). The community characteristics included distance to various facilities including highway, city center, hospital, and school. The environmental characteristics included distance to the Narayani River, presence of open drainage in the neighborhood, presence of waste collection services, collection frequency, and cleanliness of the residential area based on perceptions of respondents. The distance to the Narayani River is controlled in the model since proper embankments have not been constructed for controlling the river and the river may divert to the settlement areas anytime in an event of excessive rainfall, which is expected to lower the property value closer to the river. As waste collection services were available for most of the city area that we surveyed, albeit with different frequencies per week, we used a combination of waste collection frequency, type of service (door-to-door or at community level) and perceived cleanliness of residential areas as proxy for key environmental quality variables.

3. Results and discussion

3.1. Descriptive statistics

Tables 1a and 1b report the descriptive statistics and a description of variables. Table 1a gives information on the country-level urban sub-samples (hills and *terai)* of the NLSS III data (Fig 1). It shows that housing prices in the hills are almost twice that in the *terai*. Similarly, garbage collection and piped water distribution are better in the hills with more houses having toilet facilities in the hills compared to the *terai*. On the other hand, the *terai* has larger plot sizes and have better access to paved roads compared to the hills. Interestingly, in terms of distance, most of the facilities in the *terai* are further away when compared to the hills but, in terms of travel time, these facilities in the *terai* are closer than in the hills since, on average, roads and transportation facility in the hills are less than optimal.

The average price of a house in Bharatpur is NPR 12.7 million[3] with an average built-up area of 920 sq ft. The average age of a house is 12.50 years indicating that urbanization is a recent phenomenon in Bharatpur. In addition, around 72% of the households have a kitchen garden and are close to the highway. About 61% of the households reported a clean neighborhood, with 26% of the households reporting door-to-door waste collection services at least once a week.

3.2. Hedonic price model – Segmented market

In this section, we discuss the hedonic price estimation results using the NLSS 2010/11 data. As discussed in the methods section, we have divided the housing market into two segments, the *terai* and the hills, due to the geographical heterogeneity in housing markets. The results are reported in Table 2, where standard errors are clustered as the primary sampling units. In order to address the unobserved heterogeneity and spatial dependence of the housing price across the districts of Nepal, we have used spatial fixed effects at the district level. The spatial fixed effects results are reported in the last two columns of Table 2. We use the results reported in the last two columns for the purpose of our discussion and for computing implicit prices. In our urban sub-sample, there

[1] The NLSS III survey collected data on the self-assessed value of housing units. The survey asked each respondent the following specific question: If you wanted to buy a dwelling just like this today, how much money would you have to pay?

[2] Wards are the lowest level of the administrative unit in Nepal. In Bharatpur Metro, there are 29 wards. Out of the 29, we chose 14 wards for this study as these wards were already part of the municipality before Bharatpur became a metropolitan city in 2017. These wards are relatively more urban with higher population density.

[3] The housing price for Bharatpur in 2017 is deflated to 2014/15 price using the consumer price index in order to make the estimated results comparable with the results for the hills and *terai* sub-samples. The exchange rate in December 2014 was USD1 = NPR 102.

Table 1a
Descriptive statistics (NLSS III 2010/11 urban sub-sample).

		Hills (N1 = 839)		*Terai* (N2 = 543)	
Variable	Definition	Mean	SD	Mean	SD
Sale price	Self-assessed housing price (mill NPR)	7.64	12.1	3.73	11.4
Garbage collection (Y/N)	1 if presence of service, else 0	0.51	0.50	0.17	0.38
Cement wall	1 if house wall is cement, else 0	0.54	0.50	0.55	0.50
Living room	1 if house has living room	0.34	0.47	0.22	0.41
Plot size (sq feet)	Plot size in square feet	2199	4324	2747	5855
Cement roof	1 if roof is concrete, else 0	0.48	0.50	0.45	0.50
Iron roof	1 if roof is corrugated iron, else 0	0.39	0.49	0.25	0.43
Tile roof	1 if roof is tiled, else 0	0.08	0.28	0.23	0.42
Year_built_bf95	1 if the house is built before 1995	0.50	0.50	0.64	0.48
Water piped	1 if the house has a pipe-borne water connection	0.78	0.42	0.27	0.44
Total rooms	No. of rooms in the house	6.25	3.21	5.34	2.92
Toilet	1 if the house has toilet, else 0	0.88	0.33	0.67	0.47
Higher sec school	Distance to higher sec school	1.27	2.30	1.67	1.75
Secondary school	Distance to secondary school	0.93	4.09	1.14	1.55
Primary school	Distance to primary school	0.43	0.77	0.52	0.63
Police post	Distance to police post	1.69	3.15	1.88	2.72
Public hospital	Distance to public hospital	1.96	3.26	3.08	34.33
Bus-stop	Distance to bus-stop	0.73	1.68	1.80	2.39
Market	Distance to market	2.34	3.21	3.88	34.34
Paved road	Distance to paved road	1.73	6.69	0.97	2.14
Bank	Distance to bank	1.86	2.86	2.34	2.80

Notes and sources: Urban sub-sample of NLSS III data with owner-occupied housing units. The total sample size is 1,382 households from urban centers with complete information. Consumer price index with base year 2014/15 (=100) is used to convert the monetary value to a common metric that can be compared with information presented in Table 1b. Distances are recorded in kilometers. NLSS III 2010/11 data is obtained from the Central Bureau of Statistics, Government of Nepal.

Table 1b
Descriptive statistics (Bharatpur 2017 sample).

Variable		Mean	Std. Dev.
Housing price	Housing price (mill NPR)	12.7	8.39
Clean neighborhood	1 if the neighborhood is reported to be clean, else 0	0.61	0.49
Door-to-door waste collection	1 if there is door-to-door collection service, else 0	0.26	0.44
Waste collection frequency	1 if waste is collected at least once a week, else 0	0.27	0.44
Floor area	Floor area of house (sq feet)	919	310
Kitchen garden	1 if kitchen garden is available, else 0	0.72	0.45
No. of rooms	No. of rooms in the house	5.84	3.18
Age of house	Age of the house (in years)	12.50	10.03
Age of house squared	Age of the house squared	257	426
Concrete house	1 if house is made from concrete, else 0	0.70	0.46
Residential house	1 if the house is used for residential purpose, else 0	0.76	0.43
Pipe-borne water	1 if pipe-borne water is connected, else 0	0.68	0.46
Drainage system	1 if drainage is open, else 0	0.58	0.49
Hospital	Distance to hospital	2.39	1.42
Business center	Distance to central business district	1.50	1.30
Main highway	Distance to main highway	0.77	0.92
Main river	Distance to the main river	3.75	2.55
School	Distance to secondary school	1.48	1.02
Ward office	Distance to ward office	1.44	0.93
Police post	Distance to police post	1.61	0.86

Notes and source: Field survey 2017. Total sample size 1050 households. As we have two different years of data (NLSS data for the year 2010/11 and primary survey data for the year 2017), we used the consumer price index (base year 2014/15 = 100) to convert the monetary terms into the common metric for comparison purpose. Distances are recorded in kilometers.

are 23 districts in the hills and 19 districts in the *terai*. In addition, there are 46 municipalities (Fig 1) from 42 districts (Fig 2) in the urban-subsample. The other 33 districts either did not have municipalities during the period of the survey or had been excluded from the sample.

The regression results indicate that the effect of garbage collection on housing prices is substantial in both market segments. In the hills, the average housing price is close to NPR 7.64 million (sd = NPR 12.1 million) while, in the *terai*, it is close to NPR 3.73 million (sd = NPR 11.4 million). In both market segments, the estimated coefficients of garbage collection service are positive, large, and statistically significant with 0.29 for the hills and 0.45 for the *terai* (Model 2). These coefficients measure the effect of garbage collection at the neighborhood level but not at the household level. In neighborhoods where solid waste collection services are in place, buying a house with the given attributes would cost 34% higher in the hills and 57% higher in the *terai* in comparison with buying a similar house in neighborhoods without garbage collection services. It is to be noted that since the garbage collection services are available at the neighborhood level, the implicit prices are also measured only at the neighborhood and not at the household level. The following formulas are used to estimate the implicit prices of the different characteristics of the housing units:

Table 2
Regression results for national urban sub-sample (dep var: ln(house price)).

Variables	Hills (1)	*Terai* (1)	Hills (2)	*Terai* (2)
Garbage collection (Y/N)	0.43***	0.36**	0.29**	0.45***
	(0.14)	(0.17)	(0.13)	(0.15)
Wall cement	0.52***	0.55***	0.42***	0.51***
	(0.11)	(0.14)	(0.11)	(0.13)
Living room	0.07	0.24*	0.06	0.12
	(0.08)	(0.14)	(0.08)	(0.15)
Ln(plot size)	0.36***	0.29***	0.40***	0.33***
	(0.05)	(0.08)	(0.06)	(0.08)
Roof cement	0.75***	0.96***	0.67***	1.08***
	(0.27)	(0.26)	(0.25)	(0.25)
Roof iron	0.28	0.30	0.25	0.34
	(0.24)	(0.21)	(0.22)	(0.23)
Roof tile	0.15	0.54**	0.39*	0.74***
	(0.23)	(0.22)	(0.23)	(0.20)
Year_built_bf95	−0.12	0.11	−0.05	0.06
	(0.08)	(0.10)	(0.08)	(0.11)
Piped water	0.05	0.48***	0.12	0.32**
	(0.12)	(0.14)	(0.14)	(0.15)
Total rooms	0.08***	0.14***	0.08***	0.13***
	(0.01)	(0.03)	(0.01)	(0.03)
Toilet	0.43***	0.38**	0.36**	0.30*
	(0.15)	(0.15)	(0.14)	(0.15)
Ln(high school dist)	0.06	−0.00	0.14	0.08
	(0.12)	(0.14)	(0.14)	(0.12)
Ln(secondary school dist)	−0.18	−0.25*	−0.17	−0.17
	(0.13)	(0.13)	(0.12)	(0.16)
Ln(primary school dist)	0.01	−0.16	0.15	−0.24
	(0.12)	(0.15)	(0.11)	(0.15)
Ln(market dist)	−0.06	0.03	−0.10	−0.06
	(0.08)	(0.15)	(0.08)	(0.15)
Ln(paved road dist)	−0.10	−0.17	−0.35**	−0.06
	(0.07)	(0.20)	(0.15)	(0.19)
Ln(bank dist)	−0.41***	−0.10	−0.29***	−0.24
	(0.09)	(0.16)	(0.09)	(0.17)
Ln(police post dist)	−0.11	−0.07	0.01	−0.09
	(0.09)	(0.13)	(0.09)	(0.13)
Ln(public hospital dist)	0.01	−0.08	−0.04	−0.11
	(0.10)	(0.10)	(0.11)	(0.09)
Ln(bus-stop dist)	−0.26**	0.01	−0.18*	0.08
	(0.10)	(0.12)	(0.10)	(0.14)
Ln(municipality population)	0.22***	−0.15	0.25***	0.27
	(0.05)	(0.13)	(0.05)	(0.31)
Constant	8.36***	11.06***	7.77***	6.89**
	(0.67)	(1.43)	(0.70)	(2.94)
Dist FE	No	No	Yes	Yes
Observations	839	543	839	543
R-squared	0.62	0.63	0.65	0.68

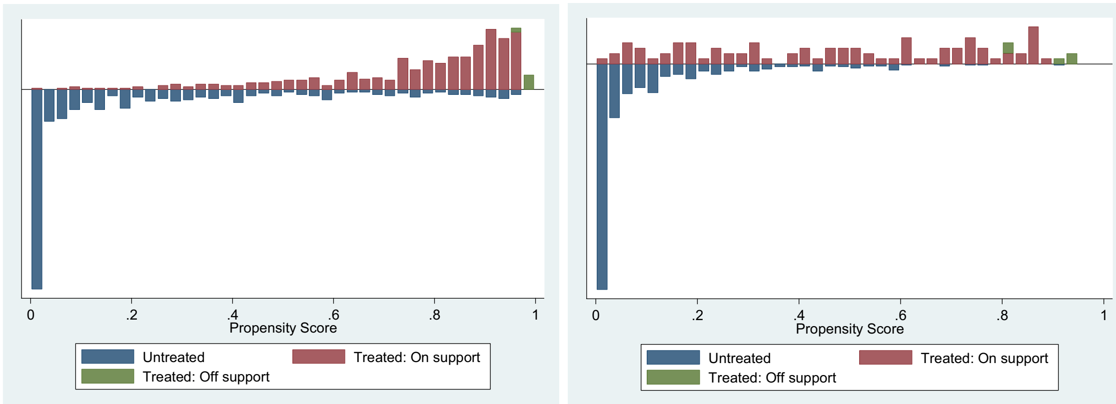
Notes: Clustered-robust standard errors are in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1. The reference wall material is other than cement (such as mud and stone and wooden wall) and the reference roof material is thatch or crop-straw. The following formulas are used for estimating marginal implicit prices from the estimated coefficients:

i) $MIP_i = 100 \times (2^{\hat{\beta}} - 1)\%$ if the attribute is a continuous variable (ln(x)) with positive effect on housing price and if we double the size of the attributes (e.g., plot size);
ii) $MIP_i = 100 \times (2^{-\hat{\beta}} - 1)\%$ if the attribute is a continuous variable (ln(x)) with negative effect on housing price and if we reduce the attribute by half; and
iii) $MIP_i = 100 \times (e^{\hat{\beta}} - 1)\%$ if the attribute is a dummy variable (e.g., presence of waste collection service in the neighborhood).

The coefficients of structural characteristics (wall materials, plot size, roof materials, and total number of rooms as a proxy for built-up area) are significant with expected (positive) sign, which is similar to what Acolin and Green (2017) have reported. In terms of geographical location, we can see that the self-reported value of the housing unit would increase by 32% in the hills and by 25% in the *terai* when the plot size of an average housing unit is doubled.

The community characteristics have mixed effects depending on the geographical location of the residential units. For example, a house in a hilly urban area that is located one kilometer away from a blacktopped road would be valued at NPR 1.6 million less than a similar house beside a blacktopped road. Similarly, a house that is one kilometer away from a bank office would be valued NPR 1.12 million less than a house located near a bank. Put differently, when the distance to a bank and a black-topped road is halved in the hills, the self-reported value of a house would increase by 18% and 22%, respectively. In the hilly urban area, both banks and blacktopped roads are about 2 km away on average from the residential units.

In the *terai*, the distance to a bank or blacktopped road is not a significant determinant of self-reported housing price after controlling for district fixed effects and structural characteristics. It may be that transportation services are not an issue in the urban *terai* whereas, in the urban hills, even if roads and banks are available in the municipalities, it may take more time to reach these facilities, mainly because of the longer waiting time for the bus due to irregularity in service (low population density being the reason for that) or the more time it would take to go to the bank on foot along the slopes of the hilly terrain.



a) Hills

b) *Terai*

Fig. 3. Common support for housing units with and without garbage collection services.

In both markets, we controlled for the municipality population to account for population pressure on the housing market as we could see from the estimated coefficients that larger population size meant higher property prices which translates into higher demand for housing units. However, this seems to be true in the hills than in the *terai*. It may be the case that in the *terai*, there is more space for urban expansion than in the hills due to steep slopes and difficulties with connecting new housing units with functional roads. Another noteworthy result is the higher value placed on pipe-borne water in the urban *terai* compared to the urban hills as households in the urban *terai* mainly get drinking water from groundwater sources using hand-pumps, which is not quite safe for drinking purposes (Thakur, Thakur, Ramanathan, Kumar, & Singh, 2011; Yadav, Dhuldhaj, Mohan, & Singh, 2011). On average, <30% of the households in the urban *terai* get pipe-borne water in our sample whereas about 78% households in the urban hills get pipe-borne water. Therefore, a housing unit with a piped water connection would be 38% more valuable in the *terai* than a similar house without a piped water connection.[4]

3.3. Propensity score matching – Segmented market

Results from the hedonic pricing models suggest a significant value for garbage collection services in urban centers across the country. However, the garbage collection services may not be introduced randomly in those cities and hence likely to be endogenous due to self-selection. In order to see the robustness of our estimates from the hedonic price models, we therefore estimate the value of garbage collection services to the residential housing units using the propensity score matching (PSM) method. For PSM, the same stratification of the housing market is maintained (hills and *terai*) for purposes of comparison. The probability of having garbage collection services is then predicted using the same covariates utilized for the hedonic regression analysis (Table 2) while the average treatment effect is estimated using two alternative approaches: kernel matching and regression adjustment. The propensity score is estimated using solid waste management services as a treatment, which is a binary variable.

The common support of the propensity score is shown in Figs. 3 (a) and 3(b) for hills and the *terai*, respectively. Fig. 3 suggests a good overlap or common support suggesting the presence of comparable housing units with and without garbage collection services in both market segments. In the hills, only 14 out of 427 treated observations are off support while there are 5 off-support observations (out of 92) in the *terai* segment.

In order to examine the reduction in bias after matching, we report the standardized bias before and after matching in Fig. 4. In this figure, it is possible to see a large standardized bias before matching in both market segments, which is reduced significantly after matching. In both market segments, the average bias after matching is around 5% only.

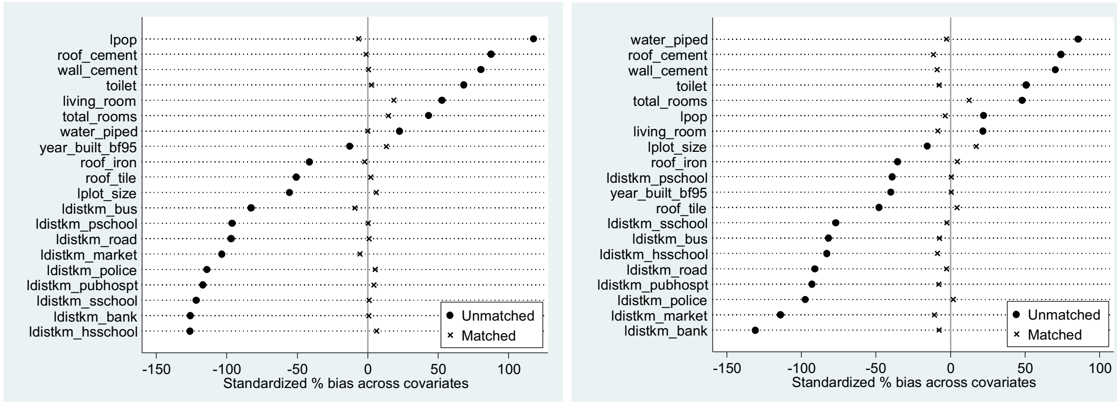
The average treatment effects (ATTs) from two different estimators (RA and kernel) are reported in Table 3 for both market segments The ATT is 0.23 and 0.28 for the hills and 0.44 and 0.50 for the *terai* (Table 3). These estimates are comparable with what we have reported in Table 2 (Model 2), suggesting that the estimates obtained from hedonic price models can be used as unbiased estimates of implicit marginal prices in the segmented housing markets.

3.4. Robustness check

To further examine the robustness of the estimated results, we use three different approaches: a) we re-estimate the hills and *Terai* models (Model 2 as in Table 2) with additional controls (water and electricity supply hours, type of stoves used by the households, and whether the household has a kitchen garden); b) we use an alternative dependent variable – the annual self-reported rental value of the house instead of the self-reported sale price; and c) we also replace self-reported rental value with actual rental value. The first case is similar to what is reported in Table 2 but with more controls. In the second approach, we use the full sample of urban households who reported the expected rental value if their houses were to be rented out. In the third approach, we use small sub-sample of renters who reported actual rent that they were paying if the house had been given on rent during the survey month. As the 'renters only' sub-sample is very small, we use renters from both urban and rural sub-samples as some of the 'rural' areas are equally urban in terms of basic facilities though not declared as 'urban' for administrative purposes.

Table 4 reports estimated coefficients for the key variables and other relevant information. Columns (1) and (2) are just the replication of what we have reported in Table 2. Column

[4] We suspect that the higher value of the municipal waste collection service may indicate some kind of sorting of different urban elements, including quality of schools, hospitals and bigger shopping malls in the same location, for which we do not have enough information. These results, however, are consistent with an existing empirical study which shows that garbage collection contributes substantially to the satisfaction of residents with public housing (Mohit, Ibrahim, & Rashid, 2010).



a) Hills b) *Terai*

Fig. 4. Standardized bias with and without matching.

Table 3
ATT of solid waste management on housing price for hills and the *terai.*

Sub-markets	RA	PSM(Kernel)
Hills	0.23	0.28
Terai	0.44	0.50

Notes: For nearest neighbor matching, we used one-to-one matching.

(3) and (4) provide the new estimates with additional controls. The last four columns report the results where the dependent variable is the annual rental price of the house, which is self-reported in columns (5) and (6) (owner occupied housing units); and actual in the case of renters only models (columns 7 and 8) (rental units). We can see that these new results are comparable (both numerically and statistically) with the results reported in the first two columns, suggesting that the results presented in Table 2 are consistent and robust which indicates that the value of solid waste management is significant and high both in terms of the value of the housing units as well as the rental value of the housing units.

3.5. Hedonic price model – Bharatpur case study

In order to understand the effect of garbage collection services on housing value, we further estimate the hedonic price model using primary data collected from the Bharatpur Metropolitan City (BMC). In BMC, the waste collection service is implemented in the entire city area. Therefore, we could not use the presence or absence of a waste collection program in the city as the key outcome variable. However, program implementation is quite heterogeneous in terms of frequency of collection, waste pick-up points, and degree of cleanliness of the neighborhood. These solid waste management related activities are the major determinants of city dwellers' willingness to pay for waste collection services in the study area (Rai, Nepal, Khadayat, & Bhardwaj, 2019b) as the solid waste pickup frequency in the city ranges from daily to every alternative day, twice a week, once a week, once in every two weeks, and only occasionally.

Given these heterogeneities, we use collection frequency as one of the key variables as defined in Table 1b. The collection service is also of two types – door-to-door collection or pick-up service from some common points in the neighborhood. In the case of the latter, households are required to take their waste up to the collection point. Therefore, another key variable that we use is whether the community is offered a door-to-door waste pick up service by the service provider. The third key variable that we use is a household's perceived cleanliness of the neighborhood (Asmawi, Mohit, Noor, Abdullah, & Paiman, 2018). The final and additional variable of interest used is the presence of an open drain in the neighborhood.

Table 5 reports the results for 5 different models where a garbage collection service is measured in three different ways: per-

Table 4
Alternative model specification and alternative measure of housing value (dep var: ln(house value or rent).

	(1) Hills	(2) *Terai*	(3) Hills	(4) *Terai*	(5) Hills	(6) *Terai*	(7) Hills	(8) *Terai*
VARIABLES	Self-reported sale price				Self-reported rental price		Actual rental price	
Garbage collection Service (coefficients)	0.29^{**}	0.45^{***}	0.28^{***}	0.44^{***}	0.22^{**}	0.43^{***}	0.26^{***}	0.31^{*}
(Standard errors)	(0.13)	(0.15)	(0.10)	(0.14)	(0.09)	(0.10)	(0.09)	(0.18)
Urban dummy							−0.11	−0.32
							(0.29)	(0.29)
Structural/ neighborhood characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yea	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dependent variable (NPR)	7.7 mil	11.4 mil	7.7 mil	11.4 mil	16,090	6,638	13,409	7,300
Observations	839	543	812	496	812	496	461	248
R-squared	0.65	0.68	0.71	0.70	0.71	0.74	0.83	0.76

Notes: Clustered-robust standard are errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All models control for structural and neighborhood characteristics including district fixed effects. The renter-only sub-sample includes households from both rural and urban area since the urban-subsample is too small for estimating district fixed effects models with sufficient degrees of freedom. In this model we also control for urban dummy to distinguish the effect of 'urban' areas.

Table 5
Estimates of hedonic price models for Bharatpur (dep var: ln(house price)).

	(1)	(2)	(3)	(4)	(5)
Clean neighborhood	0.189***			0.216***	0.217***
	(0.060)			(0.063)	(0.063)
Door-to-door collection		0.168***		0.156**	
		(0.062)		(0.061)	
Collection frequency			0.158**		0.146**
			(0.063)		(0.062)
Open drain	−0.130*	−0.115	−0.113	−0.120*	−0.118*
	(0.067)	(0.072)	(0.072)	(0.069)	(0.069)
Ln(house floor area)	0.471***	0.499***	0.501***	0.486***	0.488***
	(0.095)	(0.101)	(0.101)	(0.099)	(0.098)
Kitchen garden	0.224***	0.230***	0.230***	0.234***	0.235***
	(0.053)	(0.058)	(0.058)	(0.056)	(0.056)
No. of rooms	0.047***	0.047***	0.047***	0.047***	0.047***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
House age	0.008	0.006	0.006	0.004	0.004
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
House age squared	−0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Concrete house	0.327***	0.345***	0.343***	0.328***	0.326***
	(0.064)	(0.062)	(0.062)	(0.060)	(0.060)
Type of house - residential	−0.076	−0.078*	−0.081*	−0.085*	−0.088*
	(0.047)	(0.046)	(0.045)	(0.045)	(0.045)
Piped water	0.111*	0.123**	0.124**	0.127**	0.127**
	(0.061)	(0.058)	(0.058)	(0.057)	(0.057)
Flooding	0.070	0.047	0.046	0.069	0.068
	(0.047)	(0.050)	(0.050)	(0.048)	(0.048)
Ln(base area)	0.030	0.030	0.030	0.025	0.025
	(0.035)	(0.033)	(0.033)	(0.032)	(0.032)
Ln(hospital distance)	−0.008	0.056	0.057	0.060	0.061
	(0.078)	(0.075)	(0.076)	(0.073)	(0.073)
Ln(business district distance)	−0.100	−0.127*	−0.125*	−0.137**	−0.135**
	(0.071)	(0.065)	(0.066)	(0.063)	(0.063)
Ln(highway distance)	−0.206***	−0.244***	−0.243***	−0.209***	−0.208***
	(0.071)	(0.086)	(0.086)	(0.079)	(0.079)
Ln(Narayani river distance)	0.038	0.036	0.035	0.024	0.024
	(0.092)	(0.094)	(0.094)	(0.089)	(0.089)
Ln(school distance)	−0.002	0.004	0.002	−0.027	−0.029
	(0.120)	(0.107)	(0.107)	(0.102)	(0.102)
Ln(ward office distance)	0.028	0.077	0.074	0.086	0.083
	(0.098)	(0.091)	(0.091)	(0.089)	(0.089)
Constant	12.239***	12.046***	12.036***	12.052***	12.044***
	(0.655)	(0.675)	(0.675)	(0.661)	(0.660)
Ward FE	Yes	Yes	Yes	Yes	Yes
Observations	826	784	784	784	784
R-squared	0.489	0.497	0.497	0.507	0.506

Note: Clustered-robust standard are errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1

ceived cleanliness of the community (clean community); presence of 'door-to-door collection service'; and 'collection frequency' (at least once a week). When estimating the hedonic price models, we clustered the standard errors at the community (TLO) level. For all models, we also used ward fixed effects (our sample includes 14 wards) in order to account for unobserved heterogeneity and omitted variables that do not vary across the households within wards but may differ between wards.

Our results indicate that there is a high premium on housing prices in a clean neighborhood. The coefficients of the three variables related to solid waste management (cleanliness, collection frequency, and door-to-door collection service) are 0.15 to 0.22. The implicit prices of relevant attributes are given in Table 6.

The premium for the perceived cleanliness of the neighborhood ranges from 20% to 25% of the average housing price (NPR 12.7million) depending on the model used. For door-to-door waste collection services, the house price premium ranges from 17% to 18% while it is 16% to 17% for collecting waste at least once a week from the community (which could be either door-to-door or from a common pick-up point). Given that the average housing price is NPR 12.7 million in Bharatpur, the marginal implicit prices of waste collection services are substantial in size and statistically significant. A similar type of preference for waste collection frequency has been observed in another city in Nepal by Rai et al. (2019a).

The key structural characteristics of housing units with a significant implicit price in the Bharatpur sample include floor area, number of rooms, construction materials, house type (residential or business or combination[5]), availability of kitchen garden, and piped-water connection. Among neighborhood characteristics, distance to the main highway and to the business center were statistically as well as economically significant (the implicit price ranging from 14% to 22% of the average housing price), suggesting that the housing units located away from the main highway and the city center are less expensive. This result corroborates those of previous studies where proximity to the highway has a positive impact on

[5] In Urban Nepal, using the same housing units for business (mainly for small retail store(s)) and residential purposes is very common, where some owners set aside mainly the ground floor for renting out to those who would like to set up a retail business. Housing units with a provision of such business space are generally priced higher as owners could rent such space for business purposes and earn some cash income. In our sample, around 70% of the housing units are used for purely residential purposes while about 30% are used for both purposes.

Table 6
Implicit prices of different attributes of housing property.

Attributes	Housing market		
	Urban hills	Urban *terai*	Bharatpur
Waste collection services in the neighborhood	34%	57%	
Clean neighborhood			25%
Door-to-door waste collection service			17%
Waste collected at least once a week			16%
Open drain in the neighborhood			−11%
House with cement wall	52%	67%	39%
Residential house			−8%
House with kitchen garden			26%
House with toilet	43%	35%	
House with cement roof	95%	194%	
House with tiled roof	48%	110%	
House with piped water		38%	14%
Additional room	8%	13%	4.7%
Reducing distance to paved road / highway by half	22%		13%
Reducing distance to bank by half	18%		
Reducing distance to bus-stop by half	12%		
Doubling the plot size	32%	26%	40%
Reducing distance to CBD by half			9%

Notes: Formulas used for estimating marginal implicit prices are provided after Table 2.

property value (Seo, Golub, & Kuby, 2014). The age of the house, distance to the closest hospital[6] and distance to the Narayani River, which flows by the city, did not have a significant effect on housing price.

3.6. Marginal implicit prices

We use statistically significant coefficients of different attributes for estimating marginal implicit prices. Table 6 presents the marginal implicit prices of different attributes of housing units from all three markets – hills, *terai* and Bharatpur. The details of the method used for estimating the marginal implicit prices for different attributes is provided after the Table 2. In order to estimate the marginal implicit prices, we use the models with district fixed effects.

In Table 6, we report a) the percentage change in implicit price associated with the presence of binary attributes (e.g., waste collection service, cement wall); b) a percentage change in implicit price associated with a doubling in the value of a continuous attribute if it has a positive implicit price (e.g., plot size); and c) a percentage change in implicit price associated with halving the value of a continuous attribute if it has a negative implicit price (e.g., distance to facilities).

For the urban hills sub-sample, the implicit price of the waste collection service is 34%, meaning that a house in a neighborhood with solid waste management services would cost 34% more than a similar house without such service. The implicit price of solid waste management is higher in the urban *terai* (57%) than in the hills. This is mainly due to the fact that the urban *terai* is located on flat land with high summer temperatures where, in the absence of solid waste management services, the chances of contracting water-borne diseases would be very high. This is because, in these cities in the *terai*, the slope of land is very low resulting in water logging and flooding, a common phenomenon, during the rainy season.

[6] In Bharatpur, healthcare services are available in several places in the city since the city is a primary hub of hospitals and clinics for people living in the city and surrounding areas. The city is well connected by highways and by air, with several domestic airlines providing transportation services to the city from Kathmandu and Pokhara, the two other largest metro cities in the country.

In Bharatpur, the marginal implicit price of a clean neighborhood is 25% while it is 17% for door-to-door collection of municipal solid waste and 16% for waste collected from the doorstep at least once a week. The housing price however drops by 11% if the neighborhood is exposed to open drainage, which is basically a measure of the disamenity services of an open drain in terms of bad smell and associated problems. This finding is similar to what Irfan (2017) found in the Pakistani city of Rawalpindi. The disamenity associated with open drainage is not only the bad smell but also the possibility of an increase in water-borne diseases from blockage of the drainage system due to solid waste dumping, which would cause water logging and flooding (Pervin et al., 2020).

Another interesting result is that in the urban *terai*, a housing unit with a piped-water connection would cost 38% more than a similar house without a piped-water connection. This is mainly because the municipal drinking water supply in the *terai* covers only 27% of households with many households using ground water that has not been adequately treated for drinking purposes, which increases the risk of water-borne diseases during the rainy season. In Bharatpur, where 68% of the households are supplied with piped-water, the value of a housing unit with a piped-water connection is 14% more than a comparable housing unit without a connection. On the other hand, access to paved road, banking services and bus-stop are critical neighborhood attributes in the urban hills with significant marginal implicit prices. For example, reducing the distance to a paved (black-topped) road by half in the urban hills increases the value of a house in such a neighborhood by 22% whereas it is 13% in Bharatpur.

In terms of the rental price of an average housing unit, the marginal implicit price of solid waste collection services is 30% and 35%, respectively, in the hills and the *terai*. Although these estimates are slightly lower than those for self-reported housing price as an outcome variable, they are still significant and sizable, suggesting that both rental price and self-reported housing price increase significantly (at least by 30%) when solid waste collection services are in place in these cities.

4. Conclusion

South Asian cities have been facing tremendous challenges when it comes to managing municipal solid waste. Due to the lack of proper solid waste management services, cities have also had to deal with increasing risks of water logging and flooding when exposed to extreme events including climate change (Pervin et al., 2020). Although municipal solid waste management services are available in some cities, city residents are not always satisfied with the way the services are being delivered (Rai et al., 2019b). Study suggests that the South Asian residents prefer waste-to-enegy as one of the solutions for managing municipal solid waste better (Haque et al., 2019).

Using the hedonic price models, we estimated the implicit prices of municipal solid waste management services for three market segments: urban hills, urban *terai* and Bharatpur Metropolitan City. The estimated implicit price of the municipal solid waste management service is statistically significant and economically large for all specifications and alternative outcomes. However, there are two issues that need to be highlighted. First, it is a fact that in Nepal some form of sorting of residents has been occurring across cities, which could result in unexpected rises in property prices in anticipation of which households might be reporting expected property prices based on developments in infrastructure and quality of service in future. When a city starts installing good infrastructure and providing quality services including municipal solid waste management services to its residents, it would in turn attract more businesses and services including better quality schools, better hospitals and larger shopping malls, ultimately driving up property prices. However, our data does not provide this critical information. In Nepal, the quality of physical infrastructure, education and healthcare services is highly heterogeneous across the country, which may be true of other developing countries as well. Therefore, future hedonic price research should consider collecting such information instead of just relying on the presence or absence of certain attributes since the quality of the attributes may not be the same across cities and sub-national units.

Second, as has been seen in our data set, the municipal solid waste collection service varies at the neighborhood level, but not at the household level. Therefore, care should be taken when interpreting the results. For example, in the urban hills, it costs on average 34% more to buy a house in a neighborhood that has municipal solid waste collection services compared to buying one in a neighborhood that does not have the service. But it should be noted that this is not the same as saying that a person is willing to pay 34% more to buy a house with municipal solid waste collection services than a house without garbage collection services in the same neighborhood.

In fact, if some households are receiving solid waste management services while others are not in the same neighborhood, then the marginal implicit price of the solid waste management service would be much smaller than the case where the service is available to all at the neighborhood level. This is because an individual household would not get the benefit of living in a cleaner neighborhood if just a few households enjoy garbage collection services while other households in the neighborhood do not. What our estimated coefficient does is to capture an individual's willingness to pay to change his/her entire neighborhood from being one with no municipal solid waste management services to one with those services. This question is much more relevant from a policy perspective than a question about the change in services to a single house. Our results should be interpreted from this angle.

The results suggest that cleaning up entire neighborhoods or cities could bring large returns to home-owners in the form of higher property prices. Municipalities could point to these results as a rationale for introducing a solid waste management service fee or levying a property tax on their residents where the service has not been introduced. They may also consider revising the user fee where it is already implemented as municipality officials in the sampled urban centers are facing a resource crunch in efforts to maintain their cities' cleanliness. If a municipality already has a property tax that depends on the market values of properties, then it will also share in the financial returns from a successful improvement in waste management.

CRediT authorship contribution statement

Mani Nepal: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing - original draft, Writing - review & editing, Supervision, Funding acquisition, Project administration. **Rajesh K. Rai:** Data curation, Investigation, Project administration, Writing - review & editing. **Madan S. Khadayat:** Investigation, Data curation, Software, Project administration. **E. Somanathan:** Conceptualization, Methodology, Writing - review & editing, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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