Public Disclosure Authorized

Public Disclosure Authorized

Policy Research Working Paper 10031

Housing Demand and Affordability in India

Implications for Housing Policy

Nadeem M. Karmali
Xinyu Weng

WORLD BANK GROUP
Urban, Disaster Risk Management, Resilience and Land Global Practice
May 2022

Policy Research Working Paper 10031

Abstract

The focus of this paper is on the demand for housing in urban India. Using rental data, the paper finds that income elasticities of housing demand are high and elastic across time. Hedonic pricing regressions confirm that this high elasticity is driven by high demand for improved water and sanitation amenities that are attached to the consumption of housing. Further, the demand estimations show that rental markets in urban India and in megacities are becoming more efficient, emerging from the shadow of legacy rent control regulation and uncertainty from the past. All the results suggest that household subsidies or other demand-side interventions are less warranted, but rather investments to increase housing supply through better service infrastructure for water, sanitation, and connectivity are better uses of public resources. The analysis also provides guidelines to improve the targeting of housing programs by means testing against the income distribution. Using one such estimate of the income distribution, the paper shows that housing affordability is improving in India. In doing so, the paper highlights the methodological challenges in measuring housing affordability in developing countries.

This paper is a product of the Urban, Disaster Risk Management, Resilience and Land Global Practice. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://www.worldbank.org/prwp. The authors may be contacted at xweng@ifc.org.

The Policy Research Working Paper Series disseminates the findings of work in progress to encourage the exchange of ideas about development issues. An objective of the series is to get the findings out quickly, even if the presentations are less than fully polished. The papers carry the names of the authors and should be cited accordingly. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the International Bank for Reconstruction and Development/World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent.

Produced by the Research Support Team

Housing Demand and Affordability in India: Implications for Housing Policy

Nadeem M. Karmali
Xinyu Weng

JEL No. O18, R21, R31, R38
Keywords: Housing demand; price and income elasticities; housing amenities, hedonic regressions

This research was undertaken at the World Bank supported by funding from the Foreign, Commonwealth & Development Office through Externally Funded Output 1479. The two World Bank projects associated with this research are the First Tamil Nadu Housing Sector Strengthening Program Development Policy Loan (P172732), and the Tamil Nadu Housing and Habitat Development Project2022 (P168590), both from the South Asia Urban, Disaster Risk, Resilience, and Land Global Practice. The Task Team Leaders of these projects at inception were Yoonhee Kim (P172732), and Abhijit Sankar Ray, Angelica Nunez del Campo and Yoonhee Kim (P168590). The authors would like to thank Yan F. Zhang and other World Bank peer reviewers for comments, and Diego Sourrouille provided excellent research assistance with housing price indices.

1. Introduction

Understanding the levers that affect housing demand provides useful goalposts for shaping housing policy. There is a long history in the economics literature of estimating housing demand across the world and in developing countries (Malpezzi and Mayo 1987). In India there is a need to better understand housing demand given the dynamic nature of the housing market, and the changing paradigm shifts of housing policy (Wadhwa 1988). New microeconomic data have become available across urban India, as have improved estimation techniques to estimate housing demand. The key goals this analysis seeks to address are: (i) to estimate income and price elasticity of housing demand, with a focus on megacities across urban India; and (ii) to uncover drivers of housing demand through hedonic pricing approaches. The demand analysis focuses on renters in urban India given the relevancy of current market prices that most rent payments capture, and to understand to what extent rental markets in India have become more efficient from the legacy of rent control and other regulations. Given the focus on the role of supply elasticities in contemporary housing policy across the developed world (Gyourko and Molloy 2014), it is interesting to revisit the demand versus supply question in a developing country context. In particular, to evaluate whether demand-side subsidies are justified or if fiscal resources would be better utilized in other domains of the housing market. As an extension to estimating housing demand, the analysis also looks at the distributional aspects of housing to situate the design and targeting of housing programs through both a normative and positive perspective. The paper concludes with an exercise to measure housing affordability in India using the residual income method—more from a methodological perspective in terms of how housing affordability can be measured in a developing country context and the estimation challenges related to doing so, rather than to provide an answer to the degree of housing affordability in urban India.

This paper is structured across three main housing questions: demand estimation, distributional analysis, and affordability. Section 2 presents: the housing demand estimates for urban India, results of hedonic price regressions for renters, and estimates a new rental price index. Section 3 explores the distributional aspects of housing in urban India against the backdrop of income definitions from past and current housing programs. Section 4 explores housing affordability in India with a focus on methodologies, and section 5 concludes.

The main results of the paper (section 2) show that housing demand is high and elastic in urban India and in megacities. This high and elastic housing demand is driven by strong household preferences for improved water and sanitation facilities bundled within housing investments. This suggests that housing policy should focus more on the supply rather than the demand side, and in particular the supply of supporting housing services in water, sanitation, and connectivity more broadly. This analysis focuses on renters and the rental market in urban India. Renters represent the tenancy type of a third of urban households, while the rental market has the most reliable housing market data across the whole of urban India. Against the historical backdrop of inefficiencies and archaic regulations in rental housing markets across India, the results show convincing evidence for increasingly efficient rental pricing and continued convergence of rental to sales prices in housing in megacities. This augurs well for the enactment of the model tenancy act, supporting legislative changes and the real estate investment trust (REIT) market for the future.

The distributional analysis (section 3) shows that housing-specific household income categories used by existing housing programs in India can be better calibrated to the income distribution. This is critical across India for harmonization of income definitions, social protection and reducing fiscal leakage.

As demand for housing is high and households have a high willingness to pay for housing, it is interesting to look at how housing demand compares with housing affordability metrics. Interestingly, the affordability exercise in section 4 of the paper that uses a residual income methodology, shows improvements for renters in terms of affordability (in the same vein as poverty has decreased), but calls for better transaction data to understand housing affordability for owners.

Overall, the results demonstrate the importance of approaching housing policy in developing countries across a dynamic paradigm of supply and demand, rather than more static metrics of affordability. Urban households in India are willing to pay more for housing over time as these higher housing costs are implicit investments in the health and nutrition of their families. This is also the reason for combining demand estimates and affordability in one study, as it allows for a direct juxtaposition of housing demand and affordability given that these are intricately linked.

The analysis of affordability also shows how translating affordability paradigms for developed economies presents data and conceptual challenges when used in a developing country.

2. Housing Demand

2.1. Literature Review

Understanding housing demand is critical for a range of public as well as private sector decisions. As a result, there has been long historical interest in accurately measuring housing demand. Given the scope of government interventions in housing markets across the world starting from the beginning of the twentieth century, ensuring that housing demand parameters are accurate has had important consequences for the uptake of government programs and the efficiency of public spending. The beginning of the housing demand literature can be traced to Engel (1857) and Schwabe (1868), which started the tradition of comparing expenditure and housing demand. They found that income (or expenditure) elasticity of demand to be less than one. This later became known as 'Schwabe's Law of Rent.'

The most recent literature reviews on housing demand from De Leeuw (1971) and Mayo (1981) have been able to reduce some of the uncertainty of income and price elasticity estimates in terms of critical study design decisions such as the use of microeconomic data, the choice of functional form, adjusting for permanent income, and also for tenure choice. Overall, the literature has found that in the developed world, the permanent income elasticity of housing is on average well below one and the price elasticity is less than one in absolute value (Mayo 1981).

In the past two decades, part of the housing demand literature across the developed world has leveraged newer demand estimation systems to improve estimates of housing demand. In particular, the use of discrete choice models to categorize housing types in a flexible mixed logit framework (Rouwendal and Meijer 2001, Börsch-Supan, Heiss and Seko 2001, García and Hernández 2008). Another part of the literature has built on the unobserved differentiated products estimation techniques from the industrial organization literature (Bayer, McMillan and Reuben 2004, Bajari and Kahn 2005). Finally, in the run-up to and as a result of the global financial crisis of 2008, there has been renewed macroeconomic interest in the developed world on housing demand and the relationship between house prices and income (Gallin 2006, Holly, Hashem and Yamagata 2010). Some of these studies find that in the long run, income elasticity of housing demand is exceptionally large: Gallin (2006) finds that over 23 years, the income elasticity of housing demand is between 1.45 and 1.71. However, it is not yet clear how to reconcile time series macroeconomic estimates with microeconomic panel estimates which produce much lower estimates.

The rapid urbanization across the developing world starting in the 1960s led to the application of demand estimation techniques in the literature for developed countries to extend to cities and markets in the developing world, although the data were less rich. The seminal work from Malpezzi and Mayo (1987) demonstrates the usefulness of such demand estimates for developing country policy makers and highlights some of the critical data challenges. A number of contemporaneous studies to Malpezzi and Mayo (1987) from the Republic of Korea, El Salvador, and Pakistan (Jimenez and Keare 1984, Lodhi and Pasha 1991, Follain, Lim and Renaud 1980) build on this foundation. Overall, these studies estimate higher income elasticity of housing demand and lower price elasticity of housing demand compared to developed countries, however the range of estimates from developing countries is larger due to data and regulatory challenges in housing markets in these early studies. Malpezzi (1999) summarizes the initial housing demand literature work across developing economies in a handbook chapter from.

More recently with the growth of capital and rental markets across the developing world, new housing data have come to light which have allowed better estimates of housing demand. Studies of new mortgages in Mexico show that the estimated price elasticity is –0.3 and the estimated income elasticity is 0.8 (Fontenla and Gonzalez 2009), while recent research from Hong Kong SAR, China, and Shanghai finds slightly lower income elasticities around 0.5 (Zheng, et al. 2018, Chen and Jin 2014). There are also a series of studies from other developing countries that have been produced recently.[1]

In India, a number of studies have found high income elasticities of housing demand. Malpezzi and Tiwari (1991) estimate a parsimonious model for Bangalore, India, and find an income elasticity of 0.58. Dholakia (1982) uses aggregate macroeconomic time series data to obtain a price elasticity estimate across India of –0.33. While Tiwari and Parikh (1998) use

[1] For China, see Zhang, Li, and Kong (2016), for Ghana see Tandoh and Tewari (2016), for Saudi Arabia see Al Obaid (2020), and for Turkey see Pinar and Demir (2016) and Solak and Kabadayi (2016).

microeconomic household data to estimate an income elasticity of 0.75 and a price elasticity less than –1 across India. Tiwari, Parikh & Parikh (1999) look at Mumbai and find even higher income elasticities. Overall, these estimated income elasticities for India are higher than the median income elasticity estimate from developing countries of 0.5 (Malpezzi and Mayo 1987). However, in Ahmedabad, India, Mehta and Mehta (1987) find an income elasticity of demand for renters to be in the range 0.17–0.43, although the scope of rent control in Gujarat has been more extensive than in other states (Field, et al. 2008) which could explain this low result. There is also evidence of high income elasticities in neighboring Pakistan (Lodhi and Pasha 1991). These high income elasticity of housing demand estimates are aligned with recent wealth estimates from India that show a disproportional amount of household wealth is concentrated in housing and gold, rather than financial assets as is the case in other countries, including in China (Reserve Bank of India 2017, Badarinza, Balasubramaniam and Ramadorai 2016).

With the growth of capital markets and loosening of rent control regulations across urban India, there is a need to revisit these housing demand estimates, in particular to guide policy and to better understand contemporary demand characteristics of households across urban India.

2.2. Methodology

There are a number of methodologies to estimate housing demand and theoretical frameworks depending on the market and question at hand. The approach herein follows that in Goodman (1988) and Zabel (2004). The utility for an individual household i in market j is a function of their non-housing composite consumption (C_{ij}), housing services (H_{ij}), and demographic characteristics of the household that may affect preferences (A_{ij}).

$$U_{ij} = U(C_{ij}, H_{ij}, A_{ij}) \qquad [1]$$

For a single-period maximization, a household chooses to allocate income (y_{ij}) to C_{ij} and H_{ij}.

$$\max_{H_{ij}C_{ij}} U(C_{ij}, H_{ij}, A_{ij}) \quad s.t \quad C_{ij} + p_j H_{ij} = y_{ij} \qquad [2]$$

This maximization will then lead to the household demand function.

$$H_{ij} = H\left(p_j, y_{ij}, A_{ij}\right) \qquad [3]$$

Measuring the quantity of housing is not straightforward as this involves both a price and a total value. For those specifications herein explicitly estimate the quantity function form, market-level price indices are used to divide the value of housing by a price level for a given market. Adopting a hedonic regression framework, and letting F_n represent housing characteristics or housing amenities (such as square footage, number of bedrooms, type of water and sanitation facilities) for housing unit n. Therefore, the value of a unit n for individual i in market j consumed is:

$$v_{nj}^{i} = v\left(F_n; \beta_j\right) \qquad [4]$$

If housing amenities selected are known for each household along with the associated value of this housing, then it is possible to estimate the market-specific housing feature coefficients (β_j). This then allows for the construction of a price index for each market, using both the average value of housing amenities and the estimated hedonic value coefficients for that market. Normalizing one market and period to 100, then allows for the construction of a price index for each market.

$$p_j = 100 \times \frac{v\left(\overline{F_n}; \widehat{\beta_j}\right)}{v\left(\overline{F_n}; \widehat{\beta_1}\right)} \qquad [5]$$

Then the quantity of housing can be recovered as the value divided by this price index.

$$H_{ij} = \frac{v_{nj}^{i}}{p_j} \qquad [6]$$

Using H_{ij} from equation [6], and given that y_{ij}, A_{ij} and p_j are known, it is then possible to estimate the demand equation [3].

Estimating the demand equation requires additional choices and specifications. The literature has identified at least three critical considerations. The first is the distinction between current income and permanent income. Goodman and Kawai (1982) have pioneered the now-standard approach to use a human capital framework to estimate permanent and transitory income using household demographic variables. For developing countries there is the additional challenge that often expenditure rather than income is available at the household level. The approach used here is the Goodman and Kawai (1982) framework for permanent income-based estimates on an expenditure measure of income and also permanent income-based estimates using imputation of income from reported expenditure, this is used to address some of the omitted variable bias considerations. The second consideration is the importance of controlling for selection of tenure choice depending on renters or owners (Ermisch, Findlay and Gibb 1996). Here a Heckman (1979) selection model is used to attempt to correct for this tenure choice. The third consideration is the functional form. A log-linear functional form has often been the most expedient, although, when tested, the validity of this choice is often rejected. A log-linear functional form does allow for easier interpretations of coefficients and elasticities. Another functional form that has been used in the housing demand literature is the Box-Cox family of functional forms. This imbeds a linear, reciprocal, and logarithm functional form within its parameterization and a maximum likelihood approach is used to estimate the best functional form. The characterization of Box-Cox is:

$$\frac{y^{\theta}-1}{\theta} = \alpha + \sum_{k} \beta_k \frac{x_k^{\lambda}-1}{\lambda} + \sum_{j} \delta_j \, z_j + \varepsilon \qquad [7]$$

where $\varepsilon \sim N(0,\sigma^2)$ and θ and $\lambda \in (-\infty, +\infty)$. The dependent variable, y, is transformed by the parameter θ, while each of the transformed independent variables, x_k, are transformed by λ. There are also untransformed independent variables z_j which are either indicator variables or variables with negative support, as transformed variables cannot be negative given their exponential form. When $\theta = \lambda = 1$, the Box-Cox form becomes a simple linear equation, while when $\theta = \lambda \rightarrow 0$, the equation becomes log-linear and when $\theta = \lambda = -1$, the equation becomes the reciprocal in the dependent and the transformed dependent variables. This approach is useful as the Box-Cox estimation first begins with a likelihood estimation for θ and λ so that the most appropriate form can be selected.

The approach here is implemented across a number of steps. First a series of hedonic regressions are estimated for renters in urban India and 11 megacities across five years of data. In the first specification a log-linear form is used followed by the Box-Cox specification using housing amenities that are tailored to the developing country context. These hedonic price regressions are then used to construct a price index for 11 megacities, following which housing demand equations are estimated with specifications that incorporate both income and price elasticity. The approach runs both a log-linear and Box-Cox throughout to enable comparisons.

2.3. Data Sources

The data used to estimate housing demand are household surveys summarized below in Table 1. The National Sample Survey (NSS) are repeated cross sections (not a panel) of households across India, which focus on different topics every year. The series that are selected correspond to those that contain detail housing modules, and these occur every five years. Two supplementary household surveys from the India Human Development Survey (IDHS) series, IDHS I and IDHS II, are used to map expenditure to income as the NSS surveys do not capture household income. All of these surveys have household expenditure and household rent paid. The first two surveys also capture imputed rent for owner-occupied housing for the years 1993 and 2002. This is not available for the latter three rounds. The analysis here focused on renters first and then on owners. In these surveys, there is no measure of household wealth or housing values. Those are available in other surveys and are explored at the end of this subsection along with the imputed rent estimates for owners.

TABLE 1: DATA SOURCES FOR ESTIMATING HOUSING DEMAND IN INDIA

	NSS 49 (1993)	**NSS 58 (2002)**	**NSS 65 (2009)**	**NSS 69 (2012)**	**NSS 76 (2018)**	**IDHS I (2005)**	**IDHS II (2012)**
Household Expenditure	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Income	—	—	—	—	—	Yes	Yes
Poverty Estimates	—	—	—	—	—	—	—
Rent Paid (renters)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Imputed Rent (owners)	Yes	Yes	—	—	—	—	—
Housing Amenities	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City Identifiers	Yes	Yes	Yes	Yes	Yes	—	—
Housing Value	—	—	—	—	—	—	—
Number of Households	118,154	97,201	153,408	94,456	105,935	41,554	42,152

Note: NSS= National Sample Survey. IDHS = India Human Development Survey. NSS data are from the Ministry of Statistics and Programme Implementation in India. Each of these NSS surveys contain a 'housing condition' module. In particular, the survey names are as follows—NSS 49: Housing Condition and Migration; NSS 58: Housing Condition; NSS 65: Housing Condition; NSS 69: Drinking Water, Sanitation, Hygiene and Housing Condition; NSS 76: Drinking Water, Sanitation, Hygiene and Housing Condition. The IDHS is conducted by an Inter-university Consortium for Political and Social Research headquartered at the University of Michigan. All data are representative at the state-sector (urban, rural) level and all surveys include survey weights.

The surveys also capture household and household head demographics as well as city identifiers so that the city-level demand estimation can be undertaken. Given that the survey is not representative for all cities, the city-level analysis focusses on 11 megacities. These 11 cities were selected based on the 2011 census estimates of the largest cities in India.[2]

The results in the following subsections begin with an overview of the data and the main variables. This is then followed by hedonic pricing estimates for renters and the estimated price indices for the 11 cities across the five years from 1993 to 2018. A summary of the permanent income estimates is presented before the income and price elasticities are computed. The estimation presents both the log-linear and the Box-Cox estimates for comparison.

2.4. Housing Amenities across Urban India

A substantial part of the literature on housing in India as well as the population census is centered around the building materials of a dwelling's structure. For example, out of a total of 52.1 million units of the urban stock, the 2001 census categorized 38.9 million units of the 'residential stock' as being *pucca*.[3] This is defined as housing construction that comprises 'permanent' wall and roof materials such as concrete, stone, or wood rather than mud, tarp, or straw. This is often where the housing characteristic descriptions end in the literature on housing quality in India. This is an artefact of history when the structure was the most important signal of housing quality. Although more nuanced and updated housing characteristics are collected regularly, these are not reported or measured systematically by official reports or studies. An effort was made here to compile a more complete list of housing amenities for a more robust demand estimation and to better understand housing preferences in markets that are understudied.

Table 2 shows housing amenities at five points in time across 1993–2018 for India and urban India using household housing surveys. As has been well noted in other studies, average household size in India has been decreasing over time, from 5.0 in 1993 to 4.3 in 2018. Although the size of dwellings (in square feet) and the number of bedrooms has increased modestly over these 15 years, the per capita amount of space or bedrooms has increased due to falling family size.

---

[2] These 11 megacities are Mumbai, Delhi, Kolkata, Chennai, Bangalore, Hyderabad, Ahmedabad, Pune, Surat, Jaipur, and Lucknow. These 11 megacities had 75.7 million people in 2001 and 95.7 million in 2011. In 2011, this is equivalent to 25.4 percent of the urban India population (377 million).

[3] Data from National Housing Bank (2008). Where *pucca* is defined as a 'census house' that has both the wall and roof made of a firm construction material such as stone, cement, concrete, bricks and in the case of a roof, iron or asbestos (Office of the Registrar General & Census Commissioner India 2011). The residential stock is any 'census house' (any unit with a door and separate entrance) that is reported to be used as a residence or a mixed-use residence. This is not an estimate from a building census, but rather how the population census maps the built environment *in order* to count people.

Of note from Table 2 is the remarkable increase in quality of the water and sanitation measures. Across India, the share of households with a separate kitchen with piped water, a private flush toilet, and underground drainage has increased by a factor of 5 over these 15 years, and for urban India the increase in these indicators is more than a factor of 2. For the share with a private piped water connection or a shower in the unit, these have also increased substantially—by a factor of 3. This has been well documented from an individual access point of view (World Health Organization 2019), and particularly in the context of the Millennium Development Goals (MDGs) and the Sustainable Development Goals (SDGs), but less so from the housing perspective. Although India is on track to meet the water and sanitation SDGs, the literature, especially the health literature, continues to point out the continued need for further investments in water and sanitation given the large number of people that still lack access, in addition to water quality concerns that are important to capture (Johri, et al. 2014). Nevertheless, from a housing point of view, it is clear that there have been large physical investments into water and sanitation facilities in dwellings across India—in both rural and urban areas.

Table 2 also shows statistics for select floor, wall and roof dwelling materials. Given that more descriptive material types are available in the data, the presentation differs from the census of India approach of reporting only permanent construction materials. Across these construction material-type statistics, there have been large improvements especially in improved roofs: a trebling of dwellings across India with a cement or reinforced concrete roof between 1993 and 2018, and for urban areas this indicator has doubled across the same timeframe.

Although there is a large literature on informal housing in India—herein defined as notified slums, non-notified slums, or squatter settlements—these are not always well captured by household surveys. The data from the household surveys utilized here show that the share of households living in informal settings has decreased in urban areas from 15.4 percent in 1993 to 7.4 percent in 2018. The 2011 census estimate for the number of households living in a 'slum' was 17.4 percent (Census of India 2011).[4] The corresponding household survey percentage for the closest year (2012) from Table 2 is 11.0 percent of urban residents, confirming the known bias in household surveys to undercount informal settlements as a result of the sampling frames.

[4] A slum is defined by the census as being either a notified slum, recognized slum, or identified slum.

With continued urbanization and urban sprawl across India, the reported distance to work for urban households has increased dramatically. Therefore, although many of the other indicators from Table 2 show an improvement, these can come at a cost of longer commute times.[5] Electricity access is now almost universal across both rural and urban India.

TABLE 2: HOUSING AMENITIES ACROSS INDIA AND URBAN INDIA 1993–2018

	INDIA					URBAN INDIA				
	1993	2002	2009	2012	2018	1993	2002	2009	2012	2018
Household Size	5.0	5.0	4.8	4.5	4.3	4.7	4.5	4.2	4.1	3.8
Unit Area (sq ft)	448.6	406.8	444.8	428.1	495.5	404.4	395.3	429.8	422.0	484.4
Bedrooms	1.8	1.9	2.0	2.0	2.1	1.8	1.9	2.0	2.0	2.1
Other Rooms	0.9	1.0	1.2	1.7	1.8	1.0	1.3	1.6	2.3	2.1
Kitch. w/ Water (%)	5.0	9.2	12.3	17.1	24.3	16.9	25.3	32.1	39.7	51.6
Piped Water (%)	17.4	22.2	26.5	29.9	34.2	48.5	53.8	57.9	56.7	57.2
Flush Toilet (%)	12.4	19.5	25.2	38.7	60.9	34.0	46.8	51.1	62.3	74.7
Shower in Unit (%)	11.2	18.7	23.0	28.2	40.8	27.5	41.1	48.0	55.4	67.4
U/grd Drainage (%)	4.6	9.7	12.5	20.2	26.1	15.7	29.2	35.4	45.3	52.5
Floor: Tiles (%)	3.9	7.9	10.0	14.4	17.8	12.5	20.8	25.2	32.1	36.0
Wall: Cement (%)	5.5	6.5	9.5	5.3	16.6	14.5	11.4	18.5	8.0	23.3
Wall: Stone (%)	43.0	55.6	59.1	70.6	66.6	63.8	76.3	73.1	85.2	72.0
Roof: Cement (%)	16.1	27.2	35.1	43.2	54.2	39.2	50.9	60.0	66.2	75.8
Has Electricity (%)	49.1	64.1	75.0	85.8	95.6	82.2	91.6	96.1	97.9	99.1
Informal (%)	8.0	3.0	3.2	3.5	2.5	15.4	10.5	10.8	11.0	7.4
Dist. to Work (km)	2.1	3.6	4.5	5.3	6.3	2.9	4.8	5.4	6.4	7.8
Renters (%)	11.0	12.5	12.1	13.4	12.5	32.7	33.9	33.9	33.3	32.2
Owners (%)	83.9	83.0	85.2	83.1	85.1	57.6	60.1	61.7	61.2	63.6
Expenditure (median)	1,000.0	2,200.0	3,150.0	5,210.0	7,800.0	1,500.0	3000.0	4,500.0	7,850.0	10,800.0
Observations	118,154	97,201	153,408	95,456	105,935	43,871	41,677	56,306	42,122	42,213

Note: Data are from NSS rounds 49 (1993), 58 (2002), 65 (2009), 69 (2012), and 76 (2018). Kitch = Kitchen. U/grd = underground. Dist = Distance. Informal is either a notified slum, a non-notified slum, or a squatter settlement. Mon. Exp = monthly expenditure. Imp. Rent = Imputed Rent. All means and medians weighted by household survey weights.

The last three rows of Table 2 look at tenure type and median household income. There are some studies (Tandel, et al. 2016) that highlight a precipitous decline in rental housing as a result of policies such as rent control. The data from Table 2 and the census confirm that the share of renters across India has been stable at approximately one-eighth of all households and one-third of urban households. Others in the literature have confirmed these findings (Kumar 2016, Harish 2016). The last row of Table 2 reports the monthly median household expenditure in nominal values. Table 3 presents the same indicators as Table 2 by urban owners and urban renters. A

[5] This may not always translate directly to longer commute times due to different transportation modes available and may not correlate to distance to the central business district. However, it is a useful proxy for distance as the data show this growing over time across urban India.

conservative definition of renters is adopted throughout this paper.[6] Overall, renting households are smaller in size, occupy smaller unit sizes, and have dwellings with fewer bedrooms. Water and sanitation measures are about 10 percentage points better in owned dwellings compared to rented dwellings as of 2018, though median expenditure is higher for renters than for owners. For the years where the surveys collect both imputed rent for owners and actual rent for renters, median rents are higher than median imputed rents.[7]

TABLE 3: HOUSING AMENITIES ACROSS OWNERS AND RENTERS IN URBAN INDIA 1993–2018

	URBAN OWNERS					URBAN RENTERS				
	1993	2002	2009	2012	2018	1993	2002	2009	2012	2018
Household Size	5.3	5.1	4.9	4.7	4.3	3.9	3.6	3.3	3.3	3.0
Unit Area (sq ft)	469.8	472.3	517.0	510.3	579.9	313.1	282.9	292.9	297.5	332.8
Bedrooms	2.1	2.2	2.3	2.4	2.5	1.5	1.5	1.5	1.5	1.5
Other Rooms	1.1	1.5	1.8	2.4	2.3	0.9	1.1	1.4	2.0	1.8
Kitch. w/ Water (%)	17.1	27.9	35.7	44.1	56.3	18.4	23.5	27.7	36.2	46.9
Piped Water (%)	42.2	50.4	54.9	56.5	58.3	58.5	59.2	63.9	58.9	56.3
Flush Toilet (%)	37.1	51.7	58.5	71.6	82.6	32.1	42.1	42.1	52.1	65.4
Shower in Unit (%)	26.9	42.9	51.4	60.2	71.4	29.6	39.1	44.8	51.7	63.4
U/grd Drainage (%)	11.9	26.6	32.9	43.3	48.9	21.7	33.2	40.7	49.4	59.5
Floor: Tiles (%)	13.0	22.7	26.1	33.9	36.2	11.0	17.7	24.9	31.5	36.4
Wall: Cement (%)	13.3	10.5	15.9	7.6	22.3	16.2	12.9	23.2	8.8	25.5
Wall: Stone (%)	60.4	74.6	74.1	85.2	72.1	69.7	79.8	71.6	86.6	72.2
Roof: Cement (%)	33.8	48.4	57.2	64.7	74.3	46.6	55.5	64.9	70.4	80.0
Has Electricity (%)	77.6	89.3	95.1	97.7	99.0	89.6	95.8	98.4	98.8	99.5
Informal (%)	16.6	11.6	10.9	10.3	7.0	12.7	8.5	9.9	10.1	6.8
Dist. to Work (km)	2.9	5.0	5.8	6.8	7.8	3.2	4.7	5.1	6.4	7.8
Mon. Exp. (median)	1,000.0	2,200.0	3,100.0	5,000.0	7,570.0	1,200.0	2,900.0	3,900.0	6,150.0	10,000.0
Imp. Rent (median)	85.0	280.0	—	—	—	—	—	—	—	—
Rent (median)	—	—	—	—	—	140.0	400.0	700.0	1200.0	2,400.0
Observations	24,447	25,943	36,729	28,046	28,355	15,284	13,219	16,727	11,536	12,100

Note: Data are from NSS rounds 49 (1993), 58 (2002), 65 (2009), 69 (2012), and 76 (2018). Kitch = Kitchen; U/grd = underground; Dist = Distance. Informal is either a notified slum, a non-notified slum, or a squatter settlement. Mon. Exp = monthly expenditure; Imp. Rent = Imputed Rent. All means and medians weighted by household survey weights.

Having looked at the panorama of housing amenities over time there have been clear directions of household choice that are evident from the summary statistics. This can be formally

[6] A household is tagged as a renter if it reports a strictly positive monthly rent and reports a tenure status of either 'hired' or 'hired – employee quarters.' Newer household surveys distinguish between those renters with a formal contract and those without. Given a complete time series of contractual renters is not available, this distinction is not used in the analysis here. Owners are defined as those that report either a freehold or leasehold land ownership type for their primary residential unit. Using these tenurial definitions, there are approximately 3 percent of households that are not classified as renters or owners in each year of the surveys.

[7] It is not clear how to interpret this result in a contemporary context as the years for which imputed rent and actual rent are available are during a period in history where rent control legislation was more binding. It could be that the imputed rents captured the je dure rent regime value but the actual rents captured de facto rents, where rental control compliance was imperfect and therefore higher than regulated values.

captured—for renters—in a hedonic pricing model to better understand market valuation for such housing amenities. As housing transaction data for owning households in not available, the analysis is limited to renters. This is explored in the next subsections.

2.5. Constructing a Rental Housing Price Index

To arrive at unit housing prices, the approach here follows Goodman (1978) and Goodman and Kawai (1982). It involves estimating hedonic pricing regressions allowing for submarket segmentation across both location and time. For each of the housing amenities and housing neighborhood characteristics from Table 2, hedonic pricing regressions can help understand how rents are priced based on these reported amenities. The approach below looks at both a log-linear functional form as well as a more flexible Box-Cox parameterization to calculate hedonic prices for housing amenities in urban India based on rents.

The log-linear specification for estimating a hedonic price regression is run for households i, in each submarket, which is defined as a city j and time t pair:

$$\ln(Rent_i) = \alpha + \gamma \ln(Area_i) + \sum_k \beta_k x_{ki} + \sum_l \delta_l z_{li} + \varepsilon_i \quad \text{for each } j,t \qquad [8]$$

The x variables are housing amenity measures such as number of bedrooms, water and sanitation facilities. While the z variables correspond to the dwelling's neighborhood characteristics such as whether the unit is located in an informal settlement, the distance from the household head's place of work (a proxy for distance to the central business district), and the quality of the road to which the dwelling is connected. Given that all the housing amenity measures in Table 2 are indicator variables or have a limited number of discrete values, except for the area of the unit, the log-linear specification takes the log of area so that the coefficient on log area can be interpretated as the price elasticity for the area of the unit. All coefficients from equation [8] can then be converted to the corresponding price elasticities of housing amenities and neighborhood characteristics, for each submarket.

There is sufficient evidence in the literature that the log-linear specification for housing demand is not appropriate, but it is often used due to its implementation expediency and immediate interpretation of coefficients (Goodman 1978, Mayo 1981). As a result, a Box-Cox transformation

—which embeds the log-linear form and is a more flexible functional form—is also estimated for each submarket city j and time t pair:

$$\frac{Rent_i^{\theta}-1}{\theta} = \alpha + \gamma \frac{Area_i^{\lambda}-1}{\lambda} + \sum_k \beta_k x_{ki} + \sum_l \delta_l z_{li} + \varepsilon_i \qquad \text{for each } j,t \qquad [9]$$

The selected cities for this exercise are the 11 largest cities—or megacities—from the 2011 census.[8] Over time, these 11 cities have maintained their population ranks. As of 2011, these 11 cities had 95.7 million inhabitants, or 25.4 percent of the urban India population. As a result, there are 55 log-linear hedonic price regression estimates and 55 Box-Cox transformed hedonic price regressions. For ease of representation, pooled regressions over time and city with fixed effects are shown first. This is followed by Box-Cox transformed regressions run within years for the 11 megacities, followed by a representation of the price index across all 55 data points.

TABLE 4: HEDONIC PRICE REGRESSIONS FOR URBAN INDIA POOLED ACROSS 1993–2018

	(1) Log-Linear		(2) Box-Cox		(3) Box-Cox		(4) Box-Cox	
	β	η	β	η	β	η	β	η
Area Trans	0.33***	0.33	0.93***	0.28	0.06***	0.24	0.33***	0.24
Bedrooms	0.05***	5.20	0.18***	5.87	0.64***	21.73	0.65***	22.54
Apartment	0.07***	7.37	0.22***	7.23	0.30***	9.31	0.29***	9.03
Kitchen w/ Water	0.34***	40.10	1.19***	45.03	1.30***	46.76	1.30***	47.21
Piped Water	0.06***	5.75	0.14***	4.48	0.12**	3.72	0.12**	3.59
Flush Toilet in Unit	0.22***	25.21	0.62***	21.75	0.76***	25.30	0.73***	24.55
Shower in Unit	0.09***	9.38	0.27***	8.90	0.22***	6.93	0.22***	6.77
Floor: Tiles	0.20***	22.73	0.73***	25.73	0.38***	12.10	0.40***	12.61
Wall: Cement	0.07***	7.45	0.20***	6.40	0.07	2.16	0.07	2.21
Roof: Iron/Asbestos	0.09***	9.51	0.21***	6.81	0.02	0.48	0.02	0.66
Roof: Cement	0.20***	22.28	0.55***	19.21	0.44***	14.03	0.44***	14.15
Has Electricity	0.36***	43.90	0.70***	25.26	0.53***	17.28	0.50***	16.58
Observations	68,866		68,866		17,376		17,376	
R-squared	0.678		0.705		0.770		0.769	
Geography	Urban		Urban		Megacities		Megacities	
FE	State-Year		State-Year		City-Year		City-Year	
Years	All		All		All		All	
Lambda	—		0.01		0.49		0.18	
Theta	—		0.17		0.18		0.18	

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. FE = Fixed effects. The first columns are the coefficient estimates and the second columns are the elasticity estimates in percentage units. For area, the interpretation is a 1 percent change in area, while for the others it is a one unit increase to get the corresponding price increase in percentage. 'Area Trans' is the transformed area of the unit in square feet. For the log-linear, this is the natural log and for the Box-Cox specifications, this is the Box-Cox transformation.

[8] These 11 cities in decreasing order of 2011 population are Mumbai, Delhi, Kolkata, Chennai, Bangalore, Hyderabad, Ahmedabad, Pune, Surat, Jaipur, and Lucknow.

The first set of pooled hedonic pricing regressions are shown in Table 4. The first two columns are the log-linear specification across all renters in urban India at five points in time from 1993 to 2018, with state and year fixed effects. For each pair of columns, the first column is the coefficient estimate and the second is the elasticity.[9] The log-linear estimates show that a 1 percent increase in area leads to a 0.33 percent increase in price. The largest elasticity estimates from the log-linear specification are having a separate kitchen with water (increases the marginal price by 40.1 percent), having electricity (increases by 43.9 percent), and having a flush toilet (increases by 25.2 percent).

The subsequent columns of Table 4 perform the Box-Cox transformation for the same urban sample, followed by restricting the sample to the 11 megacities in the final two pairs of columns. The first Box-Cox estimate shows the coefficient estimate and the elasticity evaluated at the mean of the independent variables.[10] The Box-Cox likelihood estimates reject the tests for evaluating lambda at –1, 0, or 1, which confirms that the log-linear form is rejected. Nevertheless, the elasticity estimates from the Box-Cox transformation match those from the log-linear when compared at the mean of the independent variables. The area, kitchen with water, electricity, and flush toilet estimates are close in value between the two functional form choices. The last two pairs of columns restrict the data to the 11 megacities, with the last pair of columns imposing the additional constraint that lambda is equal to theta from equation [9]. This is because with smaller sample sizes for the 55 submarket regressions, fixing these allows for convergence for those markets with the smallest number of observations. The elasticity estimates in the third and fourth pair of columns are similar to the second pair of columns, although there are fewer observations for the city-level regressions. When the additional constraint for the Box-Cox transformation coefficients is imposed in the last pair of columns, the estimate of theta is the same as the unconstrained Box-Cox from the third pair of columns. The area, kitchen with water, electricity and flush toilet estimates are all among the highest elasticity estimates and are statistically

---

[9] For categorical or indicator variables, the elasticity (η) is equal to $e^{\beta} - 1$. In percentage terms, this would be $100(e^{\beta} - 1)$ For logged variables (area in this case) the elasticity is constant and is equal to the coefficient, $\eta = \beta$.

[10] For the Box-Cox transformation, the coefficient is not equal to the elasticity. The elasticity in a Box-Cox transformation is not constant and therefore needs to be evaluated a point. For a transformed variable (x_k), the elasticity is: $\eta_{x_k} = \beta_k \bar{x}_k^{\lambda}(Rent^{-\lambda})$, where $\bar{x}_k$ is the mean of the variable. For an indicator variable, the elasticity is $\eta_{\hat{k}} = \{[1 + \lambda(\alpha + \overline{AreaTrans} + \sum_{k \neq \hat{k}} \beta_k \bar{x}_k + \sum_l \delta_l \bar{z}_l)] \,/\, [1 + \lambda(\alpha + \overline{AreaTrans} + \beta_{\hat{k}} + \sum_{k \neq \hat{k}} \beta_k \bar{x}_k + \sum_l \delta_l \bar{z}_l)]\}^{1/\lambda} - 1.$

significant coefficient estimates. The notable difference is the elasticity estimate on bedrooms which is much higher in megacities compared to non-megacities in urban India.

These results formally confirm the patterns shown in Table 2 in terms of the high price elasticity of water and sanitation related housing amenities. Comparing the area and marginal bedroom elasticity estimates found above to results in the literature from Mexico, shows that owners in Mexico have a higher area elasticity and equivalent bedroom elasticity: a 1 percent increase in area increases prices (for owners) in Mexico by 0.77 percent and one additional bedroom increases prices by 19 percent (Fontenla and Gonzalez 2009). The corresponding numbers for megacities in India across five years is in the last column of Table 4: 0.24 percent for area and 22.5 percent for an additional bedroom.

Time is an important dimension for hedonic pricing estimates as dwelling types, preferences, and technologies change over time. For example, almost all dwellings in 2018 across India have electricity and therefore it is likely that the 2018 electricity elasticity estimates will be lower than those for 1993 in a framework where the estimation strategy is cross-sectional.

Table 5 estimates yearly Box-Cox transformed regressions over the 11 megacities using the same housing amenities and neighborhood variables as Table 4. This allows an identification of changing preferences over time for the housing amenities and household variables.

Table 5 shows the results of five Box-Cox hedonic price regressions for five different years for which household survey data are available for renters across 11 megacities. The area elasticity estimates over time increase through 2012 but have decreased from 2012 to 2018. The elasticity estimate for an additional bedroom has increased: starting from 11.7 percent in 1993 to 33.1 percent in 2018 for the implicit price increase for an additional bedroom. The elasticity for a separate kitchen with water has been high throughout, peaking at 74.3 percent in 2002. While the flush toilet elasticity has been high, though trending downwards, as more and more dwellings now have this across urban India. A shower in the dwelling unit has emerged over time as a new positive and statistically significant amenity in urban Indian households. Finally, both tiled floors and electricity have decreased their statistical significance and price elasticity estimates from 1993 to 2018, as these housing amenities have become more common.

TABLE 5: HEDONIC BOX-COX PRICE REGRESSIONS FOR URBAN INDIA ACROSS 1993–2018

	(1) Box-Cox		(2) Box-Cox		(3) Box-Cox		(4) Box-Cox		(5) Box-Cox	
	β	η	β	η	β	η	β	η	β	η
Area Trans	0.21***	0.21	0.48***	0.36	0.39***	0.24	0.75***	0.40	0.49***	0.17
Bedrooms	0.20***	11.71	0.98***	25.58	1.36***	27.01	1.73***	23.64	8.72***	33.05
Apartment	0.58***	36.13	0.49**	11.40	0.90***	16.03	0.40	4.69	1.22	3.61
Kitchen w/ Water	0.51***	31.05	2.59***	74.34	1.78***	33.82	4.12***	60.13	6.86***	21.98
Piped Water	−0.03	−1.63	0.23	5.33	0.56**	9.84	1.08***	13.33	0.44	1.28
Flush Toilet in Unit	0.57***	35.31	0.84***	20.50	1.99***	38.91	0.34	4.03	6.20***	20.00
Shower in Unit	−0.06	−3.21	0.20	4.57	0.59**	10.40	−0.62	−6.88	5.00***	15.81
Floor: Tiles	0.67***	42.67	0.02	0.37	0.69***	12.14	0.24	2.80	3.56***	10.84
Wall: Cement	0.09	4.79	0.41*	9.49	0.08	1.36	1.49**	18.47	−0.42	−1.21
Roof: Iron/Asbestos	0.18**	10.08	0.38	8.82	0.06	1.02	−0.33	−3.79	0.76	2.23
Roof: Cement	0.35***	20.42	0.72***	17.28	0.71**	12.63	1.43**	18.16	1.57	4.68
Has Electricity	0.45***	27.85	1.75***	50.16	3.28***	79.63	3.02*	44.33	6.83	23.03
Observations	5,643		3,134		3,919		2,082		2,598	
R-sq	0.440		0.565		0.575		0.612		0.557	
Geography	Megacities		Megacities		Megacities		Megacities		Megacities	
FE	City		City		City		City		City	
Year	1993		2002		2009		2012		2018	
Lambda	0.12		0.24		0.25		0.28		0.44	
Theta	0.12		0.24		0.25		0.28		0.44	

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The first columns are the coefficient estimates and the second columns are the price elasticity estimates. For area, the interpretation is a 1 percent change in area, while for the others housing amenities it is a one-unit increase. 'Area Trans' is transformed area of the unit in square feet.

Overall, the annual estimates show considerable differences over time, though the water and sanitation measures are still high and have had fewer rank changes over the years. By running these Box-Cox hedonic pricing regressions for each of the 55 submarkets (11 megacities and 5 years) one can estimate the average price level in a submarket by calculating the mean of the predicted price level across all observations in the submarket. This produces a price level (in nominal terms) for each submarket. Dividing all these by one city value in a single year can yield a rental price index based off these hedonic pricing regressions. Formally, the price index for each submarket is characterized by equation [5], setting the base price to be the Mumbai 1993 price.

The computed rental price index across the 11 megacities is shown in Figure 1. Over 15 years there have been large increases in nominal rental prices. Between 1993 and 2018, the city-population weighted average rental price across these 11 megacities has increased by 14.3 times. For comparison, the consumer price index in India only increased by a factor of 5.7 across the same time.

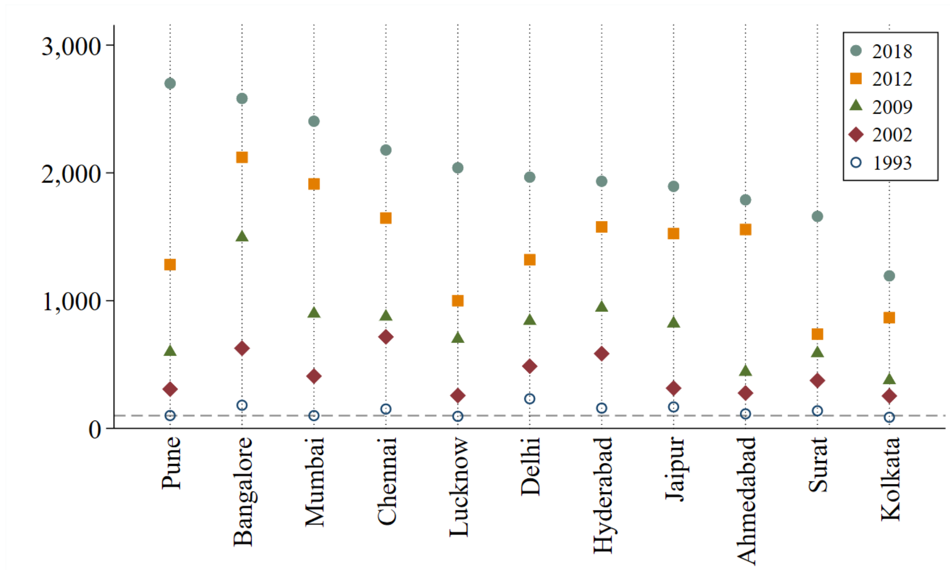
Although there has been broad price growth across the 11 megacities there are important differences within them. Most striking is the impact of rent control. India has had a long history of rent control (Alok and Vora 2011). Model rent control legislation from the national government was published in 1992 to encourage the states to adopt legislation that loosened rent control practices. Features of this model law include removing rent control from all urban towns with a population of less than 300,000, limiting the ability for tenancy to be an inheritable asset from one generation to another, and exempting rent control from new construction for a number of years after construction to encourage new investment. Only four states have adopted the recommendations of the more market-friendly model rent control legislation.[11] In parallel, there has been varied enforcement of existing rent control legislation across India, together with binding fixed nominal thresholds that are not relevant for many renters, as they are not indexed to inflation and therefore too low (Tewari and Kumar 1986). Further, most of the founding rent control legislation is only applicable for rental contracts exceeding 12 months, and as a result many contracts are shorter to avoid the applicability of rent control. In 2019, a more ambitious model

[11] West Bengal (1997), Maharashtra (2000), Rajasthan (2003), and Karnataka (2001).

tenancy act was drafted to strengthen contracts and recourse for renters, including through the creation of rental courts and rental tribunals.

The largest annual increases in the rental price index from Figure 1 are from 2009 to 2012. It is also clear that cities in states that adopted the updated and less stringent rent control legislation had higher increases in rents (Pune in Maharashtra, Bangalore in Karnataka, and Mumbai in Maharashtra). These have also been cities that have grown substantially, and so the adoption of updated rent control legislation may indeed be endogenous to city and state development. Kolkata in West Bengal has seen the most muted price increases in Figure 1. This is likely because the updated rent control legislation enacted in 1997 actually strengthened the existing provisions given, the preferences of the socialist government that was in power in the state at the time (Sengupta and Tipple 2007).

FIGURE 1: DERIVED RENTAL PRICE INDEX ACROSS 11 MEGACITIES

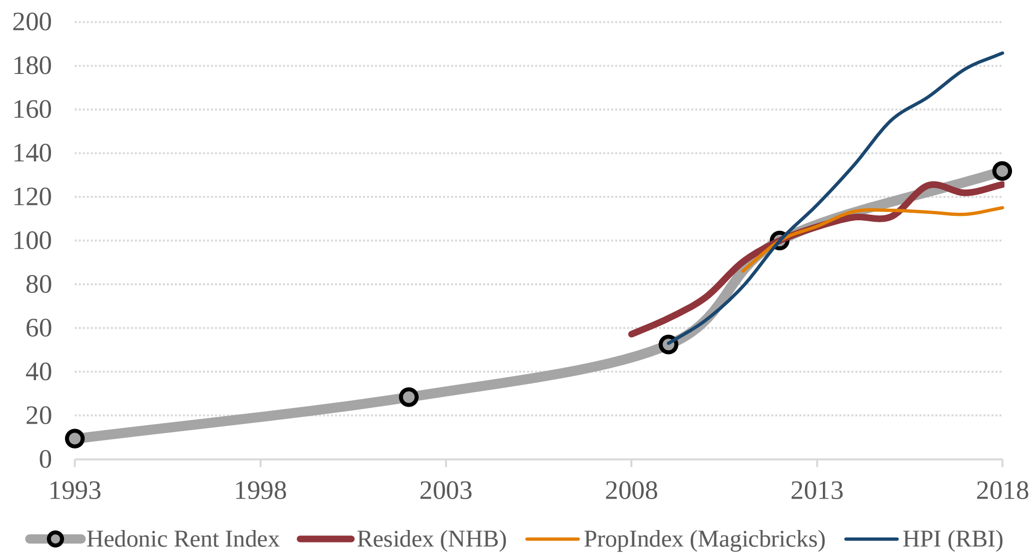


Note: Data based on hedonic regressions from Table 5 Base megacity and year are Mumbai 1993. Horizontal dotted line corresponds to the base and is equal to 100.

India is yet to develop a comprehensive house price index, although there are official indices that are regularly published and are being regularly improved (Singh 2015). One of these official indices is calculated by the National Housing Bank and is called Residex. The other was developed by the Reserve Bank of India and is referred to as the House Price Index (HPI). There are also a few private sector price indices for a select number of cities. Residex is a sales index that uses a modified Laspeyres' approach from 25 housing finance lenders. It now covers many cities and began publishing its non-pilot phase results from 2007 (Athaide 2008). The HPI uses residential real estate transaction data from real estate registration authorities, on the date of the registration. The index is constructed using a Laspeyres' weighted average methodology (Singh 2015).

The private sector also publishes house price indices. One is called PropIndex and is based on properties listed on the Magicbricks real estate listings site. The website has over 600,000 active properties posted by more than 150,000 active users in 300 cities and 10,000 localities. It covers both rental and for-sale properties, and weights are derived based on the supply in a locality. Jones Lang LaSalle (JLL) produces a Real Estate Intelligence Service (REIS) index that is constructed based on quoted for-sale prices from real estate developers.

FIGURE 2: COMPARING URBAN INDIA HOUSING PRICE INDICES



Note: Population weighted average of city house price indices. Average of six megacities: Mumbai, Delhi, Kolkata, Chennai, Bangalore, and Ahmedabad. For Residex, PropIndex, and HPI, values are annual and correspond to June values. Hedonic Rent Index is computed using household surveys at five years across 1993–2018. National Housing Bank (NHB) data from NHB. Reserve Bank of India(RBI) data from Singh (2015). Magicbrick's PropIndex is the 'Ready to Move' index prepended with the Magicbricks 2011–2015 Magicbricks index.

The hedonic rental price index constructed in this paper overlaps with Residex, PropIndex, and HPI in 6 cities that represent three-fourths of the 11 cities in terms of population percentage.[12]

[12] These are Mumbai, Delhi, Kolkata, Chennai, Bangalore, and Ahmedabad. In 2011, the population of these six cities represented 20 percent of the total urban population of India. The JLL REIS Index is only available by subscription and is therefore not compared as it was not available to the authors.

Using rolling population weights and rebasing 2012 to be equal to 100 for these four indices, Figure 2 compares them at a national average level.

The two hedonic pricing rent indices, Residex and PropIndex, track each other very well, while the municipality-sourced transaction registration data from HPI diverges after 2012. The large price appreciation across buying (Resident and PropIndex) and renting (the index developed in this paper) occurred between 2009 and 2012 across all indices. Given that Residex is a pure buyers index and that PropIndex is a hybrid, and the hedonic pricing index is a pure renters index, it is surprising that these all coincide so well. This questions the repeated assertions that the rental yield in India is low. These price indices coinciding suggests that capital markets and rental markets in megacities are more efficient and are more closely connected than previously thought. It also validates the choice of housing amenities used above in the hedonic pricing regressions.

Having constructed and evaluated a hedonic rental price index using the household survey data at five points in time, the next subsection summarizes the construction of permanent income estimates before the elasticity regressions are run.

2.6. Permanent Income Estimates

Given the variability of current incomes, and especially so in developing countries, combined with the fact that housing is a large purchase or outlay, the literature on estimating housing elasticity has encouraged the use of permanent income estimates (Lee 1968, Goodman and Kawai 1982). The most frequent approach to estimate a household's permanent income has been to use a human capital expansion of current income and use the fitted values for the permanent income and the residuals for transitory income. This is used to address some of the omitted variable bias from demand equations as current income or expenditure may not be sufficient to explain housing demand.

To estimate current income, the methodology to transform expenditure to income based on expenditure percentiles from Chancel and Piketty (2019) are used. The source data that has both income and expenditure is called the IDHS. The 2004 expenditure to income mapping is used for

1993 and 2002 data, while the IDHS 2012 expenditure to income mapping is used for the 2009, 2012, and 2018 data.[13]

Both a log-linear and a Box-Cox transformed regression of current income on social status, gender of the household head, household size, and five occupation categories are used on all urban residents, including owner occupiers and renters.[14] A single equation with state and year fixed effects produces very similar results as separate regressions by year. This are shown in Table 6. The coefficient estimates, statistical significance and goodness of fit statistics are similar to those found in the literature for India and emerging markets more generally.

TABLE 6: PERMANENT INCOME REGRESSIONS FOR URBAN INDIA 1993–2018

	(1) LL	(2) BC	(3) BC	(4) BC	(5) BC	(6) BC	(7) BC	(8) BC
HH Size	0.16***	0.29***	0.18***	0.27***	0.26***	0.11***	0.10***	0.58***
Land: Small Holder	−0.13***	−0.23***	−0.14***	−0.20***	−0.20***	−0.09***	−0.10***	−0.40***
Land: Medium Holder	−0.02***	−0.04***	−0.02***	−0.04*	0.09***	−0.02*	−0.01	−0.14**
Scheduled Tribe	−0.26***	−0.49***	−0.29***	−0.41***	−0.38***	−0.30***	−0.14***	−0.75***
Scheduled Caste	−0.25***	−0.45***	−0.27***	−0.43***	−0.41***	−0.19***	−0.17***	−0.67***
HHH Female	−0.17***	−0.33***	−0.19***	−0.35***	−0.32***	−0.14***	−0.11***	−0.48***
Occup: Manager	0.59***	1.06***	0.65***	1.35***	1.19***	0.43***	0.34***	1.15***
Occup: Professional	0.73***	1.30***	0.80***	1.20***	1.33***	0.54***	0.44***	1.78***
Occup: Services	0.15***	0.24***	0.16***	0.43***	0.41***	0.02	−0.01	0.30***
Occup: Manufacturing	0.08***	0.14***	0.09***	0.20***	0.13***	0.03*	−0.01	0.17**
Occup: Clerk	0.55***	0.98***	0.61***	0.88***	1.03***	0.46***	0.28***	1.39***
Observations	226,189	226,189	226,189	43,871	41,677	56,306	42,122	42,213
R-squared	0.670	0.709	0.669	0.429	0.471	0.404	0.409	0.331
Measure	INC	INC	EXP	INC	INC	INC	INC	INC
Lambda	—	0.09	0.01	0.07	0.05	−0.03	−0.05	0.13
Year	All	All	All	1993	2002	2009	2012	2018

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. LL = Log-linear; BC = Box-Cox Transformation; INC = Income (current); EXP = Expenditure; HH = Household; HHH = Household Head; Occup = occupation.

2.7. Housing Demand Elasticity Estimates

Given that the price index and permanent income estimates have been constructed above, all the constituents for estimating housing demand for renters in urban India are ready. The

[13] The estimation in Chancel and Piketty (2019) uses a 2011–2012 household survey from India that has both income and consumption data. A transformation function from consumption to income has a floor to impose no borrowing, so that estimated income is never less than consumption, in Chancel and Piketty (2019), this specification is referred to as the A2 estimation. The A2 curve was separately reconstructed for urban households using the same approach and same data for this paper.

[14] In regressions not reported, using age and education of the household head produce regression with similar R-squared values. As household head age and education are not available in each of the surveys, a set of independent variables that are common to all surveys are used. It should be noted that this covers some of the omitted variable bias for income or expenditure, but not other variables such as unobserved inheritances of real estate (which are common in developing countries).

estimation is performed using both the log-linear approach as well as the Box-Cox transformation in equation [3], for each year separately. This is done in Table 7 across six panels in a sequential order: I. Current Income: a regression of housing rental expenditure on current income across all urban renters; II. Permanent Income: a regression of housing rental expenditure on permanent and transitory income across all urban renters; III. Permanent Income and Selection: a Heckman selection regression of housing rental expenditure on permanent and transitory income controlling for tenure type across all urban renters, given that renters may be a different subpopulation; IV. Selection in Megacities: the same specification as III but restricted to 10 megacities;[15] V. Current Income and Prices: a regression of housing quantity (equation [6]) on current income and prices in 10 megacities; and VI. Permanent Income, Selection, and Prices: a regression of housing quantity on permanent and transitory income as well as on prices, controlling for selection into tenure type, across 10 megacities. The results are presented by year across each of these six panels. For each panel and year, two sets of columns are presented. The first column for each panel-year is the coefficient estimate of the variable referenced in the same row displaying the point estimate and its statistical significance.

The second column of each panel-year is the elasticity of these point estimates. For the log-linear form this is constant across the support of the dependent continuous logged variables, while for the Box-Cox the elasticity of the transformed dependent variable is evaluated at the mean.[16] Only income and price coefficients are presented, although the regressions contain other controls. For each year the number of urban households and the number of households in megacities is also provided in Table 7.

---

[15] Kolkata is dropped from the megacities for the elasticity estimates given that rent control has suppressed prices much more than in other cities.

[16] For the log-linear form, as the income and price independent variables are always logged, the elasticity estimate is equal to the coefficient. These are presented separately for the log-linear form for consistency with the Box-Cox presentation. For the Box-Cox transformation, the elasticity of a transformed independent variable (income measures and prices) is $\eta_{x_k} = \beta_k \bar{x}_k^{\lambda}(y^{-\theta})$. When λ=θ is imposed, this is $\eta_{x_k} = \beta_k \bar{x}_k^{\lambda}(y^{-\lambda})$.

TABLE 7: HOUSING ELASTICITY ESTIMATES FOR RENTERS IN URBAN INDIA USING A LOG-LINEAR FUNCTION

	(1) 1993		(2) 2002		(3) 2009		(4) 2012		(5) 2018	
	β	η	β	η	β	η	Β	η	β	η
I. Current Income										
Income: Current	0.68***	0.68	0.92***	0.92	0.87***	0.87	0.85***	0.85	0.87***	0.87
II. Permanent Income										
Income: Permanent	1.23***	1.23	1.29***	1.29	1.09***	1.09	1.24***	1.24	1.22***	1.22
Income: Transitory	0.60***	0.60	0.85***	0.85	0.83***	0.83	0.77***	0.77	0.82***	0.82
III. Permanent and Selection										
Income: Permanent	1.22***	1.22	1.29***	1.29	1.09***	1.09	1.24***	1.24	0.96***	0.96
Income: Transitory	0.59***	0.59	0.85***	0.85	0.83***	0.83	0.77***	0.77	0.69***	0.69
IV. Megacities										
Income: Permanent	1.22***	1.22	1.39***	1.39	1.62***	1.62	0.92***	0.92	1.16***	1.16
Income: Transitory	0.63***	0.63	0.89***	0.89	1.00***	1.00	0.85***	0.85	0.79***	0.79
V. Current and Prices										
Income: Current	0.60***	0.60	0.85***	0.85	0.91***	0.91	0.81***	0.81	0.84***	0.84
Prices	0.26**	0.26	0.04	0.04	-0.67***	-0.67	-0.47***	-0.47	-0.36***	-0.36
VI. Permanent, Selection, and Prices										
Income: Permanent	1.23***	1.23	1.54***	1.54	1.69***	1.69	0.94***	0.94	1.08***	1.08
Income: Transitory	0.62***	0.62	0.87***	0.87	0.97***	0.97	0.75***	0.75	0.78***	0.78
Prices	0.34***	0.34	-1.11***	-1.11	-1.51***	-1.51	-0.52***	-0.52	-1.12***	-1.12
Urban Observations	15,284		13,219		16,727		11,536		12,100	
Megacity Observations	11,350		7,051		9,121		4,861		5,915	

Note: * p < 0.05, ** p < 0.01, *** p < 0.001. The first columns are the coefficient estimates and the second column are the elasticity estimates. All regression are weighted by household survey weights, and contain other independent variables. Panels I –VI contain tribe, caste, gender, land ownership, household size, and state (or city) fixed effects. For the Heckman estimations, the exclusion restriction are occupation indicator variables for the household head. Robust standard errors are used. As these are different households, the fixed effects capture the between state or city differences and the robust standard errors are a conservative approach to addressing possible heteroskedasticity. Clustered standard errors are not used as the within city or state correlation in errors is less of a concern as households are sampled independently each survey round, and this is not a panel.

Table 8 presents the results for the log-linear case. Panel I is a simple log-rent on log-current income regression with state fixed effects across all of urban India, with separate regressions by year (presented as columns). Overall, these income elasticities in Panel I are high, statistically significant, but just below one, and are therefore positive but inelastic. The interpretation from Table 8 Panel I for 2018, is that a 1 percent increase in income increases expenditure on rent by 0.87 percent for the 2018 point estimate. Panel II distinguishes between permanent and transitory income using the permanent income human capital regression estimates from section 2.6. For these estimates the permanent income elasticity estimates are higher than the current income estimates, but also the transitory income elasticity estimates are high. For 2018, the interpretation is that a 1 percent increase in permanent income increases expenditure on rent by 1.22 percent, and therefore the income demand elasticity is elastic. There is a functional form challenge with the log-linear function and transitory income: the residual is in log units if the permanent income human capital regression is setup as log current income as the dependent variable, log household characteristics and the independent variables. In level space, this makes the residual the log ratio of predicted permanent income to current income. As the log functional form is not amenable to negative values, it is not possible to simply insert the actual residual level difference from permanent income estimates and current income. The practice in the literature has been to use the residual logged value instead of an untransformed level difference and then calculate the elasticity at the mean. As a result, the elasticity estimates for this type of transitory income measure are high in Table 8 as has also been estimated for owners in Mexico and renters in Hong Kong with a log-linear form (Fontenla, Gonzalez and Navarro 2009, Zheng, et al. 2018). For 2018, the transitory income demand elasticity estimates are commensurate with a 1 percent increase in transitory income (as defined as the ratio of permanent to current income), which leads to a 0.69 increase in expenditure on rent for urban India. Panel III brings in selection, using household head occupation indicator variables as the excluded set of variables from the main demand estimate. Across years, incorporating selection into rental tenancy lowers the income demand estimates for both permanent and transitory income. Panel IV restricts the sample to renters from 10 megacities where the price index used is the one constructed from section 2.5, and uses the permanent income estimates used in the panels above and the selection adjustments. This is a smaller sample, but these markets are known to have higher incomes and higher housing prices. Only the 2012 megacity permanent income elasticity estimates are lower than those across urban

India, which suggests that the income elasticity of housing demand for renters is higher in megacities. Further, the estimates (other than 2012) are all elastic as they are greater than one. Panel V begins the introduction of income and prices in one regression. It uses the simple log-linear form from Panel I, includes a price term and adjusts the dependent variable to a quantity measure of housing as per equation [6]. Comparing Panel V to Panel I shows almost no change in the current income elasticity, while the price elasticity estimate becomes statistically significant and negative from 2009 onwards. This is likely a manifestation of the unravelling of rent control regulations and the expansion of price-based rental markets across the 10 megacities. The price elasticity estimates in Panel V for the three years after 2009 are around –0.5 and are statistically significant. This means that a 1 percent increase in prices leads to a 0.5 percent decrease in housing outlay. In terms of other log-linear price estimates these are commensurate: for Mexico owners from 2003 to 2004 the price elasticity estimates are between –0.29 and –0.48. In other developing economies, Malpezzi (1999) shows that price elasticities have a great degree of variation from almost zero in the Republic of Korea study from Follain, Lim, and Renaud (1980), to much higher and close to –1 across three developing economy cities (Malpezzi and Mayo 1987). In developed economies, the estimates for the price elasticity of housing demand have been higher (in absolute value), around –0.5 for owners and renters using microeconomic data (Mayo 1981) and between –0.5 and –0.8 for the United Kingdom (Ermisch, Findlay and Gibb 1996). Panel VI introduces the price independent variable into the permanent income and selection model from Panel IV. Here the permanent income estimates are similar across Panel IV and VI, but the price estimates are more elastic compared to Panel V. So much so, that even in 2002, the price estimate is statistically significant and greater than 1 in absolute value.

There are a number of challenges with the log-linear form, and as a result a more flexible Box-Cox formulation is a superior estimation technique that nests the log-linear form. Table 8 presents the same sequences of estimates as Table 7, but using a Box-Cox functional form. All the regressions from Table 8 reject the nested log-linear function form and power functions closer to a square root function for housing and income and price variables are preferred instead, in terms of a higher log-likelihood.

TABLE 8: HOUSING ELASTICITY ESTIMATES FOR RENTERS IN URBAN INDIA USING THE BOX-COX TRANSFORMATION

	(1) 1993		(2) 2002		(3) 2009		(4) 2012		(5) 2018	
	β	η	β	η	β	η	β	η	β	η
I. Current Income										
Income: Current	0.4381***	0.6958	0.9901***	0.9145	1.7828***	0.8557	1.4971***	0.8453	11.4697***	0.8246
II. Permanent Income										
Income: Permanent	6.3662***	1.1408	19.5666***	1.2058	28.1285***	1.0177	0.3031***	1.1105	2.0753***	1.0951
Income: Transitory	0.0005***	0.0236	0.0007***	0.0236	0.0006***	0.0476	0.0004***	0.0358	0.0020***	0.0177
III. Permeant and Selection										
Income: Permanent	6.3613***	1.1399	19.6505***	1.211	28.2156***	1.0209	0.3034***	1.1118	2.0698***	1.0922
Income: Transitory	0.0005***	0.0236	0.0007***	0.0235	0.0006***	0.0476	0.0004***	0.0358	0.0020***	0.0176
IV. Megacities										
Income: Permanent	1.2221***	1.1106	1.8550***	1.2484	73.9306***	1.0192	0.7728***	1.0081	10.7192***	1.0581
Income: Transitory	0.0006***	0.0514	0.0009***	0.0627	0.0017***	0.1375	0.0005***	0.0869	0.0041***	0.0808
V. Current and Prices										
Income: Current	0.2010***	0.6092	0.1121***	0.8721	0.1019***	0.8435	0.3301***	0.8046	0.7110***	0.8109
Prices	0.0478	0.0966	0.0217	0.0955	−0.0689***	−0.3462	−0.0819*	−0.1593	0.1354	0.142
VI. Permanent, Selection, and Prices										
Income: Permanent	1.2380***	0.4739	0.2411***	1.1283	1.8407***	1.0693	0.1342***	1.0169	0.1120***	1.0335
Income: Transitory	0.0002***	0.0503	0.0001***	0.0568	0.0001***	0.1434	0.0000***	0.0823	0.0001***	0.0828
Prices	0.3994*	0.2063	0.0071	0.0213	−1.4912***	−0.9187	−0.0541***	−0.2577	−0.1182***	−0.6589
Urban Observations	15,284		13,219		16,727		11,536		12,100	
Megacity Observations	11,350		7,051		9,121		4,861		5,915	
Lambda	−0.12		0.21		-0.03		0.24		0.27	
Theta	0.14		0.29		0.4		0.37		0.56	

Note: * p < 0.05, ** p < 0.01, *** p < 0.001. The first columns are the coefficient estimates and the second columns are the elasticity estimates. All regressions are weighted by survey weights, and contain other independent variables. Panels I –VI contain tribe, caste, gender, land ownership, household size, and state (or city) fixed effects. For the Heckman estimations, the exclusion restriction are occupation indicator variables for the household head. Robust standard errors are used. As these are different households, the fixed effects capture the between state or city differences and the robust standard errors are a conservative approach to addressing possible heteroskedasticity. Clustered standard errors are not used as the within city or state correlation in errors is less of a concern as households are sampled independently each survey round, and this is not a panel.

The main presentational difference between Table 8 compared to Table 7 is that the estimates of the demand elasticities are evaluated at the mean of the all the variables, and the λ and θ estimates for Panel VI are provided.

The current income housing demand elasticities are similar across the log-linear and Box-Cox specifications and are all statistically significant and less than one. The permanent income estimates (with selection and restricting to megacities) in the Box-Cox formulation are slightly lower, all statistically significant and elastic. While the transitory income elasticity estimates are much lower because they capture transitory income defined as the difference and not the ratio of permanent and current income. Panel V estimates in Table 8 are similar for current income to Table 7, but the price estimates are lower and the 2018 estimate is not statistically significant. The preferred specification in this analysis is Panel VI of Table 8. This addresses the shortcomings of current income by using permanent income, controls for selection into tenure type, incorporates price estimates for 10 megacities and uses a functional form that is not overly restrictive. The results show that the income elasticity of housing demand in megacities across India is among the highest estimates anywhere in the world and are statistically significant. The 2018 estimate from Panel VI implies that a 1 percent increase in permanent income will lead to a 1.03 percent increase in housing demand in megacities. For all years except for 1993, the income elasticity of housing demand is estimated to be statistically significant and greater than one.[17] The price elasticity estimate for 2018 is between the minimum and maximum estimate from 2009 and 2012. These lower price elasticities (in absolute value) compared to Table 7 are reassuring. The switch in sign and statistical significance from the first two years in Table 8 provide further evidence of how rental markets (and the associated capital markets behind these) are functioning more efficiently over time. This supports the anecdotal evidence of a declining relevance and enforcement of rent control laws. It also confirms the results from section 2.5 about the price convergence between the constructed price index from section 2.5 and the existing sales-based indices in the market.

2.8. Interpretation of Housing Demand Elasticity Estimates

Across all the cuts of the housing demand estimates in the sections above, it is clear that housing demand in urban India is very high. The permanent income elasticity estimates in the

[17] To arrive at a confidence interval for the elasticity estimate, one would need to make strong assumptions about the bootstrapping approach for sampling across cities. This is omitted here.

preferred specification (Table 8, Panel VI) show elastic housing demand in the 10 megacities at 5 time points between 1993 and 2018. Such high estimates have also been uncovered in previous studies. Tiwari and Parikh (1998) use microeconomic household data to estimate an income elasticity of 0.75 for owners and 0.90 renters from 1988. Tiwari, Parikh, and Parikh (1999) look at Mumbai and find even higher income elasticities at 1.07 for renters and 1.18 for owners. The results here confirm that over time and across urban India including megacities, the income elasticity of housing demand has stayed at the elevated levels since these early estimates from 1988–1999.

It is important to distinguish the demand estimates above from the recent evidence of a concentration of wealth among households in India in illiquid assets—real estate and gold—that is not common even in other emerging markets (Reserve Bank of India 2017, Badarinza, Balasubramaniam and Ramadorai 2016). The demand estimates above are based on the behavior of renting households and therefore there is no explicit wealth creation mechanism driving the results. Globally, owner income elasticity housing estimates are indeed higher than those for renters (Mayo 1981), but the only connection here between renters and owners is in terms of substitution between the two, and in terms of rental capital markets linking rents and sales prices. Based on the above, the evidence suggests that outside a wealth accumulation or savings mechanism, the demand for housing has been very high across urban India and remains very high.

Regarding the rental price index estimates across cities, one notable conclusion is the growing efficiency of rental markets across urban India and in particular in the megacities studied here. The aggregate megacity rental price index constructed here for select cities converges to the equivalent sales-based indices that are published in India. This is remarkable and shows the waning effects of rent control and growing rental capital markets that are dynamic and priced at similar levels to dwellings for sale on a comparable basis over time. The particular price estimates for the megacities estimated here are all inelastic but higher than comparable estimates from owners in Mexico and some other developing countries, which suggests that there is more substitutability between renting and owning, but could also represent the presence of an outside option for poorer urban residents who decide to exit the urban market and consume their housing in rural areas.

The third main conclusion is the importance, in terms of willingness to pay estimates, of water and sanitation amenities to urban households across India. The rent elasticities of separate kitchens with running water, a private flush toilet, a concrete roof, and an attached shower within a dwelling have been high since 1993 across urban India. This represents a more complicated narrative of housing quality than is currently being used in terms of the permanency of the construction materials for a dwelling's wall and roof. As part of this exercise, a K-modes approach is used to categorize dwellings across both urban and rural India using a machine learning approach to classification. This is shown in Annex I. The analysis shows that a multidimensional approach to classifying urban housing can greatly improve the conceptualization of housing types beyond simple permanent versus nonpermanent construction. Given the large elasticities of water and sanitation housing amenities, these are also used in addition to the number of rooms to classify housing types across urban India in Annex I as an example of how housing typologies can be broadened to reflect updated preferences and preferences over housing amenities. These 6 K-modes categories are shown to have monotonic rent and monotonic household expenditures. Thus, they can be conceived as a graduated housing type scale. Conceptualizing housing types in such a multidimensional space can better guide how to allocate fiscal resources to housing and better guide urban planning.

Combining these strong preferences for improved water and sanitation with the demand estimates suggests that housing in India is not simply a bundle that represents shelter or area (as defined by square footage or the number of rooms). The bundling of water and sanitation amenities within a dwelling unit, represent an investment in better health and nutrition through the consumption of housing. This is aside from the clear positive externalities of living in a neighborhood with better water and sanitation overall. As a result, it is important to characterize housing demand within the preferences of wider goods than has been traditionally conceived in a developing country context.

Therefore, almost all housing supply interventions are superior to efforts to continue to increase housing demand. As housing policy in India has evolved from a provider of housing to a facilitator of housing (Ghosh 2018), an additional nuance would be to facilitate housing, if at all, more through supply side measures than the demand side. The implications for policy would be to place more emphasis on investments into services and systems (especially water and sanitation, but also transportation and other forms of connectivity including the internet). Programs such as the Environmental Improvement of Urban Slums Scheme (EUIS) that started in 1972 and the Sites and Services Scheme (SSS) that started in 1980 provided critical systems and services, including water and sanitation that are aligned with the results here (Singh, Quotidian Urban Challenges: Development, Environment and Health 2014). The more recent Swachh Bharat Mission to improve sanitation facilities from 2014 onwards falls into such investments in services and systems framework which is aligned with the housing demand estimates here. Looking forward such enabling investments into water, sanitation, and connectivity that only governments can undertake are likely a better use of fiscal resources than subsidies to urban beneficiaries.

Anecdotal evidence from rental markets in India today points to the importance of bundling car parking spaces into a dwelling unit's legal form even though a potential tenant household may not yet own a car. Such aspirational consumption or consumption of health and nutrition within a rubric of 'four walls' requires careful policy and urban design in a developing country context. The next section looks at this question from a distributional perspective to understand how such policies can be better targeted and how housing expenditure varies across the income distribution.

3. Distributional Analysis of Housing in Urban India

The demand estimates above show clear patterns over time in the marginal price estimates of housing amenities. Markets are dynamic over time and within time as individual households are in different places in their own lifecycle of housing consumption, and in the distribution of income or other socioeconomic measures. Therefore, it is useful to look at housing from a distributional lens. First, to understand and potentially improve how the myriad of housing programs offered by governments are targeted. Secondly, to understand how housing preferences across the income distribution differ both within and across time, and how this information can be used to improve the design of housing programs.

3.1. The History of Income Eligibility Thresholds for Housing Programs in India

Social protection programs around the world have significantly strengthened their targeting mechanisms using proxy means testing, poverty scorecards, and other hybrid tools to better identify vulnerable households (Alatas, et al. 2012, Skoufias, Davis and De La Vega 2001).

However, housing programs around the world, and especially in India, have been slow to adopt such tools.

Historically, housing programs in India have used their own income categorization and these have not coincided with other official socioeconomic, poverty, or marketing classification schemes.[18] The first mention of 'economically weaker sections' was from the title of a 1952 housing program for industrial workers, titled the 'Integrated Subsidised Housing Scheme for Industrial Workers and Economically Weaker Sections.' For this program, the eligibility criteria for industrial workers was a monthly income of less than INR 500 per month. This was followed by a program in 1954 titled the 'Low Income Group Housing Scheme,' where eligibility was defined at the individual level for those with an annual income of less than INR 6,000. In 1959, a program for called 'Middle Income Group Housing Scheme' was developed with an annual income eligibility range of INR 7,201–18,000. Although the 1952 and 1954 programs were differently titled and targeted, their income eligibility thresholds were almost identical. In 1952, the mean urban annual per capita expenditure was INR 338 (Basu 1971). Assuming an average urban household size of 4.7, this would yield a mean annual household expenditure of INR 1,589. This is much lower than the eligibility criteria at INR 6,000 per year and suggests that from the earliest program design in urban housing, the target audience was not for those below the mean.

Only in the 1980s did these groupings become more defined and more common acronymized terms. The Housing and Urban Development Corporation adopted the following monthly income definitions: Economically Weaker Sections (EWS) - less than INR 350; Low Income Group (LIG) - between INR 351 and 600; Middle Income Group (MIG) - between INR 601 and 1,500; and High Income Group (HIG) - above INR 1,500. This was also recognized in the national 6th Five Year Plan for the years 1980–1985. In 1988, the estimated average monthly per capita expenditure was INR 266 in urban areas, which corresponds to a household monthly expenditure level of INR 1,293. Therefore, the MIG definition from 1985 was more in line with the middle of the expenditure distribution.

[18] In 1988, the Market Research Society of India created the Socio Economic Classification (SEC), which has often been used by marketing firms in India.

A 2008 task force on affordable housing introduced two new criteria for defining affordable housing: the 'carpet area' (the livable square footage of a dwelling) and mortgage payment thresholds. The EWS and LIG categories were combined and defined across three parameters: (i) the dwelling's carpet area should be between 300 and 600 square feet, (ii) the price of the dwelling should not exceed four times the household's gross annual income, and (iii) monthly mortgage payment or rent should not exceed 30 percent of the household's gross monthly income. While affordable housing for MIG was defined as: (i) the dwelling's carpet area should not exceed 1,200 square feet, (ii) the dwelling's price should not exceed five times the household's gross annual income, and (iii) the monthly mortgage or rent should not exceed 40 percent of the household's gross monthly income. Other affordable housing definitions from income tax, goods and services tax (GST) and also housing program eligibility have used a range of income, gender, and dwelling area parameters.

Unlike many countries in Latin America, India does not have official socioeconomic categories that adjust with inflation, changes in preferences over time or location. Comparing public sector housing program eligibility in India is often not synchronized across housing-related agencies and has led to confusion in the housing market. This section provides estimates of income and housing across deciles of income for urban India to help better guide program eligibility, so that more universal socioeconomic categories can be conceived that are well grounded in the income distribution data and are harmonized across agencies and in the regulatory framework.

3.2. Household Characteristics and Housing Amenities across the Income Distribution

Grounding all eligibility criteria at the household level has become a cornerstone of most developing country project and program design. This is even more pertinent for housing given that households share housing, and housing is likely one of the few goods where consumption is shared across all household members. To construct income deciles, household expenditure data from a 2018 microeconomic survey is used along with an estimated transformation function of expenditure to income from Chancel and Piketty (2019). These deciles are constructed separately for urban India and for the 11 megacities and are summarized in Panel A of Table 9.

TABLE 9: HOUSEHOLD INCOME, HOUSEHOLD CHARACTERISTICS AND HOUSING AMENITIES BY INCOME DECILE, URBAN INDIA 2018

	Total	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Panel A: Income (medians)											
Urban India											
Monthly Expenditure	10,800	3,500	5,500	7,500	9,000	10,000	12,000	14,250	16,500	20,000	25,000
Monthly Income	10,800	3,500	5,500	7,500	9,000	10,000	12,119	15,884	19,971	25,885	36,102
Annual Expenditure	129,600	42,000	66,000	90,000	108,000	120,000	144,000	171,000	198,000	240,000	300,000
Annual Income	129,600	42,000	66,000	90,000	108,000	120,000	145,426	190,613	239,649	310,615	433,222
Megacities											
Monthly Expenditure	14,000	4,500	7,000	10,000	12,000	13,000	15,000	17,000	20,000	23,000	30,000
Monthly Income	15,330	4,500	7,000	10,000	12,119	13,765	16,841	20,774	25,885	32,070	44,158
Annual Expenditure	168,000	54,000	84,000	120,000	144,000	156,000	180,000	204,000	240,000	276,000	360,000
Annual Income	183,960	54,000	84,000	120,000	145,426	165,177	202,096	249,285	310,615	384,841	529,898
Panel B: Household Characteristics and Housing Amenities (means)											
Urban India											
HH Size	3.8	1.7	2.6	3.4	3.7	3.9	4.2	4.4	4.6	4.7	5.1
HH Head Age	45.1	36.0	41.0	42.8	44.4	44.6	46.2	46.8	48.4	50.0	51.6
Kitchen with Water (%)	51.6	19.6	26.0	32.7	40.0	47.8	53.1	63.0	69.8	80.4	88.3
Roof: Cement (%)	75.8	66.9	66.0	65.7	69.2	74.0	76.4	81.0	83.3	85.9	91.5
Shower in Unit (%)	67.4	39.4	49.2	54.9	58.3	67.6	70.4	76.3	80.3	87.0	93.2
Flush Toilet (%)	74.7	39.5	55.6	64.5	72.9	75.3	81.8	85.3	87.7	91.2	95.3
Quality Index (0–1)	67.4	41.4	49.2	54.5	60.1	66.2	70.4	76.4	80.3	86.1	92.1
Owners (%)	63.6	38.3	57.1	61.7	65.9	65.6	67.8	66.5	68.5	71.8	74.5
Renters (%)	32.2	37.7	37.2	34.0	32.4	32.6	30.9	32.5	30.7	27.4	25.2
Megacities											
HH Size	3.6	1.5	2.3	3.1	3.7	3.8	4.1	4.2	4.3	4.4	4.9
HH Head Age	43.1	33.3	38.5	39.4	43.0	43.2	43.8	45.4	48.2	48.7	49.8
Kitchen with Water (%)	58.0	26.0	28.0	39.1	50.0	54.7	61.7	72.6	82.9	84.3	90.7
Roof: Cement (%)	81.6	73.5	69.2	77.2	77.4	81.2	80.4	84.8	88.7	92.0	94.5
Shower in Unit (%)	74.9	46.6	53.4	65.4	74.5	73.7	80.1	85.7	89.5	92.2	94.6
Flush Toilet (%)	74.0	37.9	57.4	65.0	72.2	74.8	80.8	84.2	87.9	92.1	94.3
Quality Index (0–1)	72.1	46.0	52.0	61.7	68.5	71.1	75.7	81.8	87.2	90.2	93.5
Owners (%)	52.9	23.3	39.1	44.9	56.7	54.9	52.6	62.5	66.4	64.6	70.9
Renters (%)	43.0	52.8	53.6	53.3	41.5	44.2	46.5	36.4	32.3	35.3	28.5

Note: Data are from NSS 76. Income estimates use the IDHS 2012 data to map expenditure to income. HH = household. Quality index is a simple average of four indicators above: kitchen with water, cement roof, shower in unit, and a private flush toilet in unit. Deciles are ranked lowest to highest, D1 is the lowest decile and D10 is the highest decile.

The 10 deciles are constructed by ranking each urban household's income in an ascending order with the use of household survey weights. The deciles for the megacities are constructed within the megacity households and so these are deciles within megacities. The 2021 projected urban population of India is 469 million people and the 11 megacities here represent an estimated 119 million people. Therefore, each of these deciles represent approximately 47 million people in the case of the urban deciles, and almost 12 million people for the megacity deciles. These are very large numbers and are commensurate with the sizes of some countries. Therefore, although the decile construction helps dissect the population, the remaining cells are not small and not as homogenous (from a standard deviation perspective) as deciles in other countries.

Panel A of Table 9 shows the median income by income deciles as well as the overall medians in the column titles 'Total.' The median is preferred to the mean for income data given the large right tails, right skew, and lognormal distribution of income found in many countries. For 2018, the median monthly income is INR 10,800. Given that the preferred transformation of expenditure to income from Chancel and Piketty (2019) assumes no dis-savings, the expenditure and income estimates are identical for the first five deciles.

A substantial amount of work has been undertaken in recent years in the literature on generating global income and wealth distributions, but the focus has been squarely on inequality measurement and estimating top incomes or top wealth (Davies, Sandström and Wolff 2011, Lakner and Milanovic 2016). Less is known about income at lower deciles and the literature still favors using expenditure for lower-income populations, especially in developing countries where income data are not part of an annual tax reporting exercise.

From Table 9 the median annual household income for the ninth decile is INR 310,615, which is close to the current EWS upper threshold for a housing program that provides subsidies for mortgages called the Pradhan Mantri Awas Yojana-Urban (PMAY-U) Credit Linked Subsidy Scheme (CLSS).[19] As with the earlier EWS thresholds, this EWS threshold includes all urban households up to the 84th percentile.

[19] The current thresholds are: EWS households with annual income below INR 300,000 and a carpet area of less than 30 m^2; LIG between INR 300,000 and INR 600,000 and a carpet area of less than 60 m^2; MIG-I between INR 600,000 and INR 1,200,000 and a carpet area of 160 m^2; and MIG-II between INR 1,200,000 and INR 1,800,000 and a carpet area of less than 200 m^2.

The megacity income distribution is to the right of the urban India income distribution. The median monthly household income in these 11 megacities in 2018 was INR 15,330. Although it is not evident from a visual inspection of the deciles, the available data point to a lower standard deviation of income among the megacities, though given the difficulty in measuring top incomes (which are higher in megacities) this may not be an accurate reflection of the data. However, for the median income within these deciles, mismeasurement of top incomes is not a concern.

Panel B of Table 9 looks at household characteristics and housing amenities across the same deciles for urban India and for the megacities. These variables in Panel B of Table 9 are a subset of those presented across time in Table 2, and are presented as means as most of the variables do not display systematic skewedness. Although poorer households in India are larger than non-poor households, there is a clustering of small households at the lower end of the income distribution: the mean household size in the first decile is 1.7 people in urban areas and 1.5 people in megacities. There is therefore an important distinction to make between household income and per capita income or expenditure. For each of the first three deciles, the poverty rate within these deciles is evenly spread at a quarter each. This is because poverty is measured on a per capita basis while household size is important for total household income or consumption. Construction of per capita deciles is also feasible, but then classifying rents and mortgages at the household level requires extra care when household size needs to be accounted for in rents or mortgages. As a result, given the functioning of housing and rental markets, it is preferrable to use a household lens in constructing income deciles, while remaining cognizant that the 'poorest' households as measured by per capita metrics are not all concentrated in the first household income decile.[20] Further, what is particular to developing urban areas is the pattern of household size due to migration. Parts of families—usually the adult income earners—may migrate to a city and thereby create small urban households not through fertility choices but through migration. This growth over income deciles is also evident in the average age of the household head from a lifecycle income perspective: the average across urban India is 45.1 years while for the first decile it is 36.0 in urban areas and 33.3 in the megacities. Four key housing amenities with high price elasticities from Table 2 are summarized by decile, including a simple average of the presence of these four amenities termed as a Quality Index that ranges from zero to one. These four housing amenities

[20] This is also the approach in Mexico and other emerging markets.

are: a kitchen with running water, a cement roof, a shower in the unit and a private flush toilet. Across both the urban and the megacity income distribution there is a strong upward slope—these are all normal goods—as income rises (across the population, at a fixed point in time), the penetration of these housing amenities increases. This is a similar though separate point than an increase over time from Table 2. Each of these housing technologies have been available since 1993 and have been desired by all households across time and within income. The steepest 'slope' of these housing amenities is a kitchen with running water with a 68.7 percentage point difference between the tenth and first deciles, followed by a private flush toilet and a shower in the unit. The patterns across megacities are better overall, as the Quality Index is on average 5.1 percentage points higher than for urban India, though the slopes are similar.

The final two rows in Panel B of Table 9 look at the housing tenure across the income distribution. The survey data also capture an 'other' category and so the sum of owners and renters is not equal to 100 percent. The share of renters in urban India in 2018 (as reported above) is a third, but it is higher in the megacities at 43.0 percent of households. Over time in these 11 megacities, the share of renters has grown by 5.7 percentage points since 1993, while the share in urban areas has remained flat. This growth has not come from owners but rather from the 'other' category and is likely a transition into more formal rental agreements in these megacities. There is a steep decline in the share of renters across the income distribution, though in the tenth decile renters are still a quarter of the households. Conversely, there is a large increase in ownership, starting from a low base of just 38.3 percent in urban areas and 23.3 in megacities in the first decile. These trends have remained stable and represent typical lifecycle and asset accumulation patterns.

The data above have shown that across the income distribution there are important dimensions and trends that require careful attention. Miscalibration of eligibility criteria has and can continue to lead to inefficient targeting in India (Wadhwa 1988). Oversimplifying tenure choice or housing preferences can also lead to an underappreciation of the dynamic nature of housing markets, and how the objectives of households in an emerging market keep evolving as amenities which may be standard in a developed economy enter a household's affordability radar. This is particularly the case for water and sanitation amenities, which have strong demand across time and by income at a point in time. These are clear normal goods and should shape policy makers decisions on public investments. This section concludes with an analysis of actual rents and actual housing valuations by income deciles. These are the actual prices paid for a flow of housing (rent) or the market value of household's primary dwelling in 2012–2013. The next section continues this theme and looks deeper at affordability.

3.3. Housing Valuations and Rents across the Income Distribution

Table 10 presents actual appraised housing valuations for owners and actual rents paid by renters for a single year (2012) where the housing valuation and rent data coincide. There is updated 2018 renter information presented in Annex II.

Table 10 is divided in two panels, Panel A looks at urban India and its income deciles, while Panel B summarizes the same variables across the megacities. Within Panel A, there is a steep gradient in housing value: it is a factor of 10 in terms of the valuation between the tenth and first decile, but after adjusting for the median housing area by income decile, this ratio changes to just 3. The median 2013 housing value per square foot across urban India was INR 1,723. In terms of median housing valuation to annual income, the ratios for urban India are in the high single digits. This is much higher than developed economies—the average in the United States is 2.6, although in some markets this has been increasing. For renters, housing areas are smaller than owners, and the ratio between rent per square foot in the tenth decile compared to the first decile is more than four times. The median rent per square foot across urban India was INR 6. What is striking about Table 10 is how median rents to income do not decrease by decile for the first five deciles, and only from the sixth decile onwards does a small decrease manifest. Part of this may be mismeasurement of income, but it has also been seen in other studies in India (Malpezzi and Tewari 1991). Indeed, Malpezzi and Mayo (1987) note that across developing countries, rent-to-income ratios do decline, but as countries and cities get richer, rent-to-income ratios increase with income. This is also the case in urban India across 1993–2018, but for the lower deciles of income there is little to no change in rent-to-income ratios. This is likely due to overcrowding, and worse water and sanitation conditions (including in slums) so that as income increases from very low levels, households spend more on housing to improve their living conditions. This is another manifestation of high housing demand and can be analyzed through quintile regressions at different points in the income distribution. Estimates across the income distribution in Hong Kong show that income elasticity increases across the income distribution.

TABLE 10: RENTS AND HOUSING VALUATION BY INCOME DECILE, URBAN INDIA 2012–2013

	Total	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Panel A: Urban India											
Owners											
Value (INR, thousands, median)	980	340	400	474	527	735	939	1,060	1,400	1,800	3,200
Area (sq ft, median)	592	344	398	420	441	495	538	592	667	807	1,087
Value per sq ft (INR, median)	1,723	1,115	1,103	1,143	1,255	1,516	1,656	1,847	2,020	2,365	3,127
Value to Annual Income (median)	8.3	9.9	7.5	7.2	6.9	8.4	9.3	8.6	8.7	8.6	8.4
Renters											
Rent (INR, median)	1,500	500	800	1,000	1,300	1,500	1,750	2,000	2,500	3,380	6,000
Area (sq ft, median)	240	130	160	190	216	230	249	350	350	422	560
Rent per sq ft (INR, median)	6.0	3.8	5.1	5.4	5.6	6.0	6.6	6.0	6.9	7.3	10.5
Rent to Monthly Income (%, median)	20.0	20.8	21.7	20.6	21.7	20.0	19.6	18.4	18.0	16.4	17.5
Panel B: Megacities											
Owners											
Value (INR, thousands, median)	2,000	890	1,050	1,200	1,000	1,500	1,072	1,650	2,250	3,150	5,000
Area (sq ft, median)	452	291	377	323	312	420	344	441	538	678	969
Value per sq ft (INR, median)	4,376	2,223	3,097	4,532	3,019	4,645	3,948	4,140	4,566	4,938	4,845
Value to Annual Income (median)	13.0	22.0	18.8	16.7	12.2	15.9	9.3	11.9	12.8	13.8	11.8
Renters											
Rent (INR, median)	2,000	500	1,100	1,500	2,000	2,000	2,500	3,500	4,000	6,000	9,000
Area (sq ft, median)	225	111	140	152	180	268	280	316	381	460	600
Rent per sq ft (INR, median)	8.8	5.1	8.3	8.5	10.3	8.2	7.7	10.5	8.8	11.4	13.3
Rent to Monthly Income (%, median)	21.2	18.8	23.1	25.0	25.0	18.4	20.2	22.5	19.8	19.5	20.6

Note: Data are from NSS rounds 68 (expenditure) and 70 (wealth). NSS 70 does not contain estimates of income and a distance and regression approach is used to impute income from household asset holding and demographic data. All means and medians are weighted by survey weights.

For urban and megacities in India, quintile housing demand regressions for 2018 renters at the 25th, median and 75th percentiles show a more horizontal pattern with very similar income elasticities (just above one), but the price elasticity only becomes negative and significant at higher incomes. This latter result is consistent with rent control being more binding for lower rents.

Panel B considers the same variables for megacities and shows that median housing valuations per square foot are 2.5 times larger than those of urban India, while median rents per square foot are 46 percent higher. The implied annualized capitalization rate between rental and sales markets in the megacities at the median valuations is 2.4 percent. This has been increasing over time and demonstrates how rental markets are becoming more efficient over time in urban India and especially in megacities.

This section has taken a positive, rather than normative, approach to report on housing outcomes across the income distribution in India. There are clear patterns that coincide with the high demand for housing as well as for water and sanitation amenities. Further, there is evidence that rental markets are improving in terms of efficiency. The next section looks at housing affordability in urban India against this backdrop.

4. Housing Affordability in India

4.1. Introduction

Housing affordability has become a popular topic; however, its measurement and policy response are not always straightforward. In the developed world, some have questioned housing affordability's axiomatic foundations (Linneman and Megbolugbe 1992), while there is growing consensus that a main challenge for the affordability of housing in the developed world is the role of regulation and geography in reducing housing supply (Glaeser and Gyourko 2003, Saiz 2010). There are several national and international attempts to measure affordability, and many of these rely on housing expenditure to income ratios against a threshold (McKinsey Global Institute 2014). The literature on housing affordability across developing countries is limited, and the extent to which existing affordability paradigms from developed countries are useful for developing countries has recently been explored (World Bank 2020).

As a result, most studies on housing affordability are country specific and rely on policy-driven thresholds and criteria. By far, the largest literature documenting housing affordability is from the United States and Australia. In the United States, there is a large literature in documenting housing affordability outcomes across cities, income, and race (Quigley and Raphael 2004, Millennial Housing Commission 2002). In Australia, the topic has received substantial empirical as well as methodological attention (Gabriel, et al. 2005, Gan and Hill 2009, Wood, Ong and Cigdem 2014, Yates and Gabriel 2006). The United Kingdom, the Netherlands, and Canada are another set developed economies that have systemically documented affordability in the housing literature (Milligan 2003, Haffner and Boumeester 2015, Haffner and Boumeester 2010, Moore and Skaburskis 2004, Stone 2006).

In the developing world, China and Malaysia have been the most studied (Chen, Hao and Stephens 2010, Yang and Chen 2014, Hashim 2010, Suhaida, et al. 2010). Some cross-country analysis from Africa has been undertaken using standardized housing expenditure surveys, but it is not clear what drives these cross-country differences (Lozano and Young 2014). The range of these studies demonstrate the lack of international comparability on the subject and the ongoing search for an easily replicable approach across countries (World Bank 2020).

Driven by prudential banking regulation, by far the most common approach is to measure affordability as housing expenditure over income, or the expenditure to income ratio. This debt service concept has grown in popularity globally, although the prevailing thresholds between 20 and 40 percent lack simple interpretations and have been critiqued (Mayo, Malpezzi and Gross 1986). In many developing countries, definitions of minimum housing or of inadequate housing have been developed based on housing structures and these definitions often include the materials of the dwelling as well as the type of water and sanitation options for households (UN-Habitat 1996). Such considerations have also been considered for the Millennium Development Goals (MDG) and Sustainable Development Goals (SDG). However, these infrastructure-based measures often do not afford an understanding of adequate housing or a standard of housing that is household-centric. For example, a standard often used across India is whether the roof and the walls of a dwelling are made of permanent construction materials. This is a binary standard and does not capture any of the characteristics of those living in the dwelling, such as the number of household members. It is difficult to translate these prevailing infrastructure-based standards into an affordability paradigm as there is insufficient information in such a standard to create a value-based basket of housing consumption that is commensurate with a household's income.

For real estate sales, an indicator of affordability that is often used is the price-to-income ratio, which captures the selling price of a dwelling and the buyer's income. This is also referred to as the median multiple when using industry rather than individual data and is the ratio of the median house price divided by the median household income in a housing market (similar measures for urban India are presented in Table 10). The residual income methodology measures the available income for housing expenses after other essential expenditures have been considered (Stone 2006). This approach reverses the order of claims to household income and prioritizes other expenditures to avoid conflating high housing costs with ability to pay. Dynamic approaches have also been developed to understand the varying ability to afford buying a house in terms of the initial down payment and the mortgage payments using a value-at-risk approach to capture the time value of money (Gan and Hill 2009). Finally, several indices have been developed around the world to track affordability. Some of these are wage based, while other take housing amenities or transportation into account. There are a very few studies that have looked at housing affordability in India. These studies have focused on either measuring the elasticity of housing demand (Tiwari and Parikh 1998) or have focused largely on slums (Ahmad, Choi and Ko 2013). Given that housing demand is so high in India, a natural extension is to understand how, in the context of high demand, do households rank in terms of their expenditure on housing against different affordability standards. The approach here focuses on the application of the residual income methodology to affordability, but other metrics are also explored in doing so.

4.2. The Residual Income Methodology

What has now become known as the residual income approach (Stone 2006) to measuring housing affordability has a long history due to the inherent confusion between *standards* and *indicators* for any ratio approach (Newman 1971, Lowry 1971, Stone 1975).[21] More recently, Kutty (2005) operationalized a residual income standard for the United States with the non-housing standard set at two-thirds of the federal poverty threshold and applied it to compute what she calls 'housing-induced poverty.' This highlights one challenge in operationalizing this approach:

[21] See Rapkin (1957) for a discussion of this confusion.

selecting a non-housing standard. The second challenge is estimating personal taxes, as most of the income data from the developed world is before-tax income, but the standard is conceptualized as an after-tax income standard. In the United States, the non-housing standard has been estimated either as a fraction of the poverty threshold or by explicitly removing housing and tax allowances from official family budget standards in a manner that accounts for household size.[22]

Operationalizing such an approach for developing countries presents additional challenges. First, most developing countries' household surveys are expenditure based, although there are notable efforts to produce income and wealth estimates globally (Lakner and Milanovic 2016, Davies, Lluberas and Shorrocks 2017). Second, to the authors' knowledge, there are no official budget standards in developing countries that are not national poverty lines. Third, it is difficult to obtain capital market values and prices from owner occupiers across the developing world to convert housing stock values to flows. The reason why stocks need to be converted into flows is that affordability is based on income and not wealth. The canonical residual income methodology for developed countries uses median mortgage payments for a given household size to convert housing values to monthly flows for new mortgages – as new mortgages is where most of the interest in housing affordability is in the developed world. Imputed rents for owner occupiers can also be used, and this approach is used herein as a comparison. This subsection addresses these three challenges for India using a range of data sources. As income taxes form a much lower percentage of tax revenue in developing compared to developed countries (Bird and Zolt 2005), income taxes are not considered in this estimation for India.

4.3. Data Sources

Several data sources are used to arrive at the housing affordability estimates for two points in time that are commensurate across owners and renters. The data used for the demand estimates above have a longer times series but are biased toward data points for renters rather than owners. There are no known available data sources on housing transactions, and therefore housing valuations are used instead. The data used for the affordability analysis are microeconomic housing surveys that are representative at the state level. These are summarized in Table 11.

[22] See Stone (2006), pp. 168–171 for a detailed discussion of these approaches in the United States.

A range of data sources is therefore used across owners and renters in India to calculate affordability using the residual income approach. Notably, there are no surveys with the requisite rent, expenditure data, and poverty data that include housing amenities such as size in square foot or other amenities.[23] As a result, comparison across surveys controlling for these housing amenities is not possible as was undertaken for the elasticity estimates above and is another reason why the elasticity estimates above focused solely on renters.

TABLE 11: DATA SOURCES FOR ESTIMATING HOUSING AFFORDABILITY IN INDIA

	NSS 59 (2003)	**NSS 61 (2005)**	**NSS 68 (2012)**	**NSS 70 (2013)**	**IDHS I (2005)**	**IDHS II (2012)**
Household Expenditure	Yes	Yes	Yes	—	Yes	Yes
Household Income	—	—	—	—	Yes	Yes
Poverty Estimates	—	Yes	Yes	—	—	—
Rent Paid	—	Yes	Yes	—	Yes	Yes
Imputed Rent	—	Yes	Yes	—	—	—
Housing Values	Yes	—	—	Yes	—	—
Select Mortgage Parameters	Yes	—	—	Yes	—	—
House Size in Square Foot	—	—	—	—	—	—
Number of Households	143,285	124,644	101,662	110,800	41,554	42,152

Note: NSS= National Sample Survey. IDHS = India Human Development Survey. NSS data are from the Ministry of Statistics and Programme Implementation in India. The IDHS is Inter-university Consortium for Political and Social Research headquartered at the University of Michigan. The expenditure NSSs are rounds 61 and 68. The debt and investment surveys are rounds 59 and 70. All data are representative at the state-sector (urban, rural) level and all surveys include household survey weights.

4.4. Non-Housing Budget Standards for India (2005 and 2012)

There is no official budget standard for India, like most developing countries, that provides a clear breakdown across different household expenditures for different family sizes. Constructing one for this exercise would be beyond the scope of the task at hand. The approach here begins with India's official poverty line to arrive at different budget standards. India adjusted its methodology for poverty estimation in November 2009 (Government of India 2009). The expert group that adjusted the poverty methodology was chaired by Professor Suresh Tendulkar, and so the current poverty estimation is also commonly referred to as the 'Tendulkar poverty line.'

The expert group made three main adjustments to the existing poverty methodology. The first was a departure from caloric intake-based poverty estimates. The second was to adopt a 'mixed reference period' consumption profile for households which accounts for total annual consumption of durable goods, education and health expenses expressed as a monthly outlay. The

[23] The expenditure data do have some measures of water and sanitation but are not as extensive as the housing surveys.

third was to anchor the new consumption-based poverty estimates on the existing 2004–2005 caloric intake-based urban poverty headcount number of 25.7 percent (Government of India 1993). In effect, the expert group ranked the urban households by per capita expenditure using a mixed reference period of recall and tagged households as poor if they were below the 25.7th percentile. Therefore, the poverty line basket was anchored on the existing urban poverty rate and translated to a per capita consumption value of goods and services across urban India. To translate this poverty line basket to each state and sector (urban and rural), a set of median prices of food, beverages and tobacco, fuel and light, clothing, footwear, entertainment, personal care items, miscellaneous goods, miscellaneous services, and durables were used.[24] It is important to note that rent, transportation, and taxes were not deflated by regional price indices and entered into the poverty line basket at the observed share. The result of this exercise was an average (across states) poverty line of INR 606.7 in urban areas and INR 499.9 in rural areas on a per capita monthly basis for 2004–2005. Annexure E of Government of India (2009) lists the consumption share of various commodity groups around the poverty line for urban areas and finds that 'rent and conveyance' amounted to INR 30.7 per month or 5.3 percent of per capita consumption at the poverty line (this includes many owner-occupied households with zero rent).

The existing poverty methodology does have its shortcomings especially in terms of lower calory thresholds at the poverty line and a higher rural poverty rate (Swaminathan 2010), but it does provide a framework to arrive at a non-housing budget standard (NHBS) in the spirit of Budding (1980), Dolbeare (1966), and Kutty (2005). Alternatively, using a minimum caloric intake-based poverty line as the provenance to construct an NHBS requires the estimation of non-food non-housing consumption, which is more convoluted and has recently been adopted for Pakistan (World Bank 2021).

One critical shortcoming of the official consumption data from India is the lack of reliable information on imputed rent for owner occupiers. Deaton (2005) shows that much of the difference between consumption gross domestic product (GDP) and consumption from household surveys in India can be attributed to imputed rent. The approach herein to constructing the NHBS, therefore, adopts the actual per capita rent expenditure from the decile around the poverty line to arrive at

[24] A total of 176 items are in the poverty line basket (Government of India 2009).

NHBS at the state and sector (urban and rural) level. Household consumption data from 2012 for the second decile of per capita expenditure show that 15.9 percent of urban households are renters. Of these households, the median rent to expenditure ratio is 13.2 percent. This is higher that the value from Annexure E of Government of India (2009) of 5.3 percent as it excludes the zero actual rent for owner occupiers.

4.4.1. Steps for Calculating the Non-Housing Budget Standard

The NHBS is constructed using two expenditure surveys: one from 2005 and the other from 2012. Two years are selected as these are the latest available expenditure surveys and they align with the dates of two wealth surveys that capture primary residence values. The budget standard is calculated using nominal data, as the actual rent and housing valuation data used in the subsequent subsections are also nominal values. The following are the detailed steps for calculating the NHBS:

1. For each household expenditure survey, restrict the data to urban households, those households that report their tenure status as 'hired' and report a non-zero rent expenditure. This definition of a renting household is therefore the intersection of the de jure and the de facto renters, and this is the most conservative estimate of the renting subpopulation.[25]
2. Using the Government of India (2009) poverty methodology, identify the urban per capita expenditure deciles that correspond to (i) the official poverty line and (ii) 1.5 times the official poverty line.
3. For each of these deciles, calculate the actual expenditure on rent for renters.[26]
4. Subtract the mean actual rent expenditure corresponding to the per capita poverty threshold expenditure decile from the state's per capita poverty threshold. When the poverty threshold is the official poverty line, this NHBS is referred to as the Low NHBS.

[25] The expenditure surveys do not have additional categories such as employee quarters or whether the household has a formal rental contract.

[26] For 2005, the rent share of expenditure for the third decile is 12.5 percent. The third decile corresponds to the poverty rate for 2005. For 2012, the rent share of expenditure for the second decile is 13.0 percent. The second decile corresponds to the poverty rate for 2012. Including other housing expenditure—household fuel, light, and water—increases the share to 23.8 percent in 2005 and 23.4 percent in 2012. The approach here does not include fuel, light, and water as the mortgage imputation is a pure housing expense, and therefore to be able to compare housing in terms of rent only, the former is selected.

When the poverty threshold is 1.5 times the official poverty line, this standard is referred to as the Moderate NHBS.

5. Given the per capita Low and Moderate NHBS, these are then presented for households of different sizes using a simple linear expansion of household size.[27] Presenting affordability by household size is common as budget standards in developed economies vary by household size.

TABLE 12: NHBS BY HOUSEHOLD SIZE FOR URBAN INDIA (INR, NOMINAL)

	Household Size					
	1	**2**	**3**	**4**	**5**	**6–10**
Panel A: 2005						
Poverty Line	607	1,213	1,820	2,427	3,034	4,854
Low NHBS	530	1,060	1,590	2,120	2,650	4,240
1.5 × Poverty Line	910	1,820	2,730	3,640	4,550	7,281
Moderate NHBS	772	1,545	2,317	3,090	3,862	6,179
Panel B: 2012						
Poverty Line	1,060	2,120	3,180	4,240	5,300	8,479
Low NHBS	914	1,829	2,743	3,657	4,572	7,315
1.5 × Poverty Line	1,590	3,180	4,770	6,359	7,949	12,719
Moderate NHBS	1,382	2,763	4,145	5,527	6,908	11,053

Note: Data are from NSS rounds 61 (2005) and 68 (2013). Each cell is the average of a state-specific monthly urban threshold. There are 35 states in both 2005 and 2012. A new state (Telangana) was formed in 2014 and therefore does not affect this data. The starting point is the official state poverty line, from which an estimated housing cost is subtracted based on actual rent from renter. The last column is averaged over states and five household sizes. The Low NHBS corresponds to the poverty line and the actual rent of renters in the corresponding decile of poverty for the year. The Moderate NHBS corresponds to 1.5 times the poverty lines and the actual rent of renters in the corresponding decile of 1.5 times the poverty line for the year. Numbers are rounded and may not exactly equal household size multiplied by the first column.

Table 12 shows the results of the NHBS calculations averaged across states for urban areas. As the poverty line in India is different by state and by sector (urban and rural) there is no single national poverty line. Panel A shows the results from 2005 and Panel B for 2012. For 2005, the average Low NHBS is INR 531 per person per month in urban India. The average Moderate NHBS, corresponding to 1.5 times the poverty line, is a higher standard at INR 777 per person per month, and therefore more households will fail to achieve this higher standard. For a household size of 2, the 2012 average Low NHBS is INR 1,751 per month. Although the nominal values between Panel

[27] As India now uses a total consumption-based poverty line, all official poverty calculations are undertaken on a strict per capita rule. No equivalence scales are used. This is because equivalence scales are more often used with caloric consumption given the different and well-known daily calory thresholds for different ages. Although total consumption is likely to be different by age or demographic composition of a household, there is less consensus on what these weights should be and how they differ across countries.

A and Panel B of Table 12 are almost double across 2005 to 2012, these are a manifestation of higher prices: poverty in urban India has decreased from 25.7 in 2005 to 13.7 percent in 2012.

4.5. Operationalizing the Residual Income Approach for Renters and Owners

4.5.1. Steps for Estimating Housing Affordability for Renters

A number of studies have distinguished between renters and owner occupiers for the residual income methodology to measure housing affordability.[28] One of the main differences of the operationalization between owners and renters is that the owner calculation usually involves calculating a monthly maximum mortgage payment based on the value and mortgage of a dwelling, and therefore the owner affordability results are presented by household size instead of dividing mortgage payments by the number of household members. Given that imputed rent data is of questionable quality, the approach here first uses appraised housing value for owners rather than imputed rent. Imputed rent estimates for owners are presented in section 4.7.2. As less than 10 percent of households in the asset and liability survey (which contains the appraised market value of a household's primary dwelling) have current mortgages, the analysis here for owners considers all owners and not just current mortgage holders. This is a shortcoming of the analysis as reliable transaction data are not available. As with the elasticity estimates, the renter affordability estimates are the preferred specification here. Below are the detailed renter steps.

1. Define a renter household as one that reports its tenure status is 'hired' and lists a strictly positive rent. This is therefore the intersection of de jure and de facto renters and is the most conservative definition of this subpopulation.
2. For each renter household map its Low and Moderate NHBS from the state in which the household resides. These standards are also mapped across years, as the NHBS change each year.
3. Using the approach developed in Chancel and Piketty (2019) for India, convert reported household consumption to estimated household income.[29]

[28] For example, see Stone, Burke, Ralston (2011) for Australia.

[29] The estimation in Chancel and Piketty (2019) uses a 2011–2012 household survey from India that has both income and consumption data. A transformation function from consumption to income has a floor to impose no borrowing, so that estimated income is never less than consumption; in Chancel and Piketty (2019), this is specification is referred to as the A2 estimation. The A2 curve was separately reconstructed for urban households using the same approach and same data for this paper.

4. For each household, calculate the maximum incomes available for housing as the difference between the estimated household income and the Low and Moderate NHBS. As there are two different NHBS levels, maximum income housing allocations are calculated for each household in the data at each NHBS level. For those households whose income is below either of these thresholds, the maximum income to housing is set to zero.[30]
5. Assess the actual rent of each household against the three ceilings: (i) maximum rent under the Low NHBS, (ii) maximum rent under the Moderate NHBS, and (iii) maximum rent under the 30 percent rent-to-income threshold. The three corresponding affordability metrics are named (i) unaffordable at Low NHBS, (ii) unaffordable at Moderate NHBS, and (iii) unaffordable at the 30 percent rule.
6. The results are presented for all renter households and then by renter households by household size.

4.5.2. Steps for Estimating Housing Affordability for Owners

The operationalization of the residual income approach is extended to owner occupiers using an asset and liability household survey where housing and land values were appraised by professional appraisers. In general, the literature has viewed these wealth and asset value estimates from India as very reliable (Badarinza, Balasubramaniam and Ramadorai 2016). These owner estimates suffer from appreciation in market values as households who do not have current mortgages do not have an outlay. However, the affordability approach here is to both establish a standard and also assess the data to measure affordability. Finally, it is standard to convert housing values to flows using stylized mortgage parameters in such affordability exercises (Yates and Gabriel 2006). The mortgage parameters for India are derived from the survey and used for all households. Individual mortgage parameters are incomplete as the tenure was not asked in the questionnaire and is therefore derived through a regression. Below are the detailed owner steps.

[30] In addition, a ratio housing income allocation as 30 percent of the calculated household income, as an additional affordability benchmark for each household in the data is calculated.

1. Define an owner occupier household as one for which the value of its primary residential real estate is greater than zero.[31]
2. For each owner occupier household, map its Low and Moderate NHBS from the state in which the household resides. These standards are also mapped across years.
3. Using a range of techniques, obtain a measure of household income using the available indicators in the wealth surveys. For the 2003 wealth survey, there is an expenditure variable and this is mapped to income using the approach developed in Chancel and Piketty (2019) for India applied to a household survey from 2014 to convert reported household consumption to estimated household income.[32] For the 2013 wealth survey, there is no reported measure of expenditure. So a distance-based matching technique on 23 demographic, socioeconomic, and asset ownership variables is used to obtain an estimate of income and a Box-Cox regression of expenditure on these variables.[33]
4. Using average mortgage parameters for the survey years, the value of the residential real estate is converted to an imputed monthly mortgage payment.[34] Each household is therefore assumed to be able to obtain the same mortgage parameters, which is unrealistic but sufficient for an analysis across all households.
5. For each household, calculate two maximum incomes available for housing as the difference between the estimated household income and the Low and Moderate NHBS. As there are two NHBS, two maximum income housing allocations are calculated for each household in the data. For those households whose income is below either of these thresholds, the maximum income to housing is set to zero.[35]
6. Assess the imputed mortgage of each household from the value of its primary real estate against the three ceilings: (i) maximum monthly mortgage payment under the Low

[31] In both the 2003 and 2013 debt and investment surveys, this definition of owners corresponds to share of owners in adjacent household surveys which specifically ask for the tenure status of the household. Further, the reported size of residential real estate (in square feet) in the wealth survey also matches with the reported owner household square feet from adjacent housing surveys.
[32] See footnote 29.
[33] The NSS wealth surveys do not ask for household income and therefore this mapping needs to be estimated. The technique uses two separate household surveys (NSS 70 from 2012 and IDHS II from 2012) over a common support of 23 variables to obtain an income (IDHS II) value for each household wealth value (NSS 70). The technique is a Mahalanobis distance matching sliced and matched on sector of the households residence (urban or rural). The function is the ratio of the mean wealth and mean income for each percentile.
[34] For 2003, the mortgage parameters used are a loan-to-value multiplier of 70 percent, an annual interest rate of 14 percent, and a mortgage tenor of 120 months. For 2013, the mortgage parameters used are a loan-to-value multiplier of 70 percent, an annual interest rate of 11 percent, and a mortgage tenor of 120 months. These are derived from the median reported terms in these surveys for those households that are current on their mortgages.
[35] A ratio housing income allocation as 30 percent of the calculated household income, as an additional affordability benchmark for each household in the data is also calculated as with the renter approach.

NHBS, (ii) maximum monthly mortgage payment under the Moderate NHBS, and (iii) maximum monthly mortgage under a 30 percent rule. The three corresponding affordability metrics are named (i) unaffordable at Low NHBS, (ii) unaffordable at Moderate NHBS, and (iii) unaffordable at the 30 percent rule.

7. The results are presented for all owner households together and by household size.

4.6. Housing Affordability Results for Urban India

Table 13 shows the results using the two NHBS from Table 12 across four surveys: two surveys that cover renters and two surveys that cover owner occupiers in urban India. Panels A and C correspond to renters and Panels B and D correspond to owner occupiers. The first column combines all households, while the other columns summarize outcomes by household size. In urban India, renters have a lower incidence of poverty, almost a third lower than owners. For both owners and renters, and across urban India in general, poverty has halved between 2004 and 2013. Although incomes have increased across the decade, the key feature of Table 13 is that estimated affordability for renters is significantly lower than for owners. This can be seen by observing the median rent in Panels A and C compared to the median imputed mortgages. Median rents are about an eighth of either median income or median expenditure. However, median imputed mortgages are more than half of median income or median expenditure. As a result, the affordability measures at the bottom of each panel are much higher for owners than for renters. This could be due to several reasons, including differences between permanent income and reported income, incomplete capital markets, legal ambiguity with rental contracts especially in terms of eviction regulations, and real estate asset values that have grown substantially in recent years. As noted above, the owner estimates are not based on transaction data and suffer from an appreciation bias.

The median house value in 2013 is four times higher in nominal terms compared to 2004, while the median rent is only twice as much in nominal terms. Operationalizing the residual income approach in a developing country with incomplete capital and rental markets (in particular a very low rental yield) and rapid real estate asset value appreciation (also a manifestation of incomplete capital markets) presents its challenges. However, this does point to the difficulties in ownership in India and why first-time home buyers in India are on average older than in other countries (Badarinza, Balasubramaniam and Ramadorai 2016).

TABLE 13: HOUSING AFFORDABILITY ESTIMATES FOR URBAN INDIA

	All	Household Size					
		1	2	3	4	5	6–10
Panel A: 2004 Renters							
Poverty Headcount (%)	13.8	1.1	2.1	7.6	9.5	15.9	26.2
1.5 × Poverty Headcount (%)	39.7	5.4	16.5	27.4	33.3	47.9	60.9
Expenditure (INR, median)	3,733.1	1,715.2	2,742.8	3,595.9	4,594.8	4,506.4	5,394.2
Income (INR, median)	3,733.1	1,715.2	2,742.8	3,608.0	5,055.9	4,901.3	6,324.5
Rent (INR, median)	500.0	250.0	500.0	600.0	650.0	600.0	500.0
Rent to Income (%)	13.6	14.9	18.9	16.2	14.4	12.9	10.2
Unaffordable at Low NHBS (%)	13.7	1.4	3.5	8.6	10.5	16.8	23.0
Unaffordable at Mod. NHBS (%)	34.6	6.3	19.9	28.0	32.0	41.7	45.5
Unaffordable at 30% Rule (%)	3.0	5.9	11.4	5.5	2.3	1.5	0.8
Panel B: 2003 Owners							
Poverty Headcount (%)	32.6	18.7	20.1	20.1	24.5	33.9	49.0
1.5 × Poverty Headcount (%)	59.6	43.8	40.3	46.0	50.5	62.0	77.8
Expenditure (INR, median)	3,500.0	900.0	2,000.0	3,000.0	3,500.0	3,600.0	4,000.0
Income (INR, median)	3,624.0	900.0	2,000.0	3,000.0	3,624.0	3,912.1	4,285.2
Housing Value (INR, median)	200,000.0	85,000.0	200,259.0	200,221.0	225,000.0	195,000.0	200,000.0
Imputed Mortgage (INR, median)	2,173.7	923.8	2,176.5	2,176.1	2,445.4	2,119.4	2,173.7
Unaffordable at Low NHBS (%)	73.9	81.0	81.5	72.3	71.4	72.1	74.7
Unaffordable at Mod. NHBS (%)	86.3	90.6	90.3	83.6	83.3	85.2	88.9
Unaffordable at 30% Rule (%)	76.0	84.2	86.8	81.6	78.2	72.8	70.1
Panel C: 2012 Renters							
Poverty Headcount (%)	5.6	0.8	0.7	1.0	3.0	7.2	15.7
1.5 × Poverty Headcount (%)	22.7	3.2	4.7	7.7	18.3	32.0	47.4
Expenditure (INR, median)	7,864.4	3,751.6	6,266.9	8,783.3	9,385.8	10,017.8	10,751.7
Income (INR, median)	7,864.4	3,751.6	6,266.9	9,053.3	9,937.9	10,969.5	12,071.5
Rent (INR, median)	1,200.0	500.0	1,200.0	1,500.0	1,500.0	1,500.0	1,500.0
Rent to Income (%)	15.3	14.7	19.3	17.9	15.7	14.0	12.3
Unaffordable at Low NHBS (%)	5.6	1.0	1.1	1.4	3.4	6.9	15.0
Unaffordable at Mod. NHBS (%)	22.1	3.2	5.4	9.5	20.5	31.8	39.7
Unaffordable at 30% Rule (%)	4.9	5.3	13.2	7.9	4.6	3.3	1.2
Panel D: 2013 Owners							
Poverty Headcount (%)	5.6	0.0	0.0	0.0	0.2	1.8	13.5
1.5 × Poverty Headcount (%)	35.3	0.0	0.4	8.1	20.2	35.8	57.0
Expenditure (INR, median)	8,272.3	2,862.9	5,520.4	7,128.4	8,615.1	9,002.5	9,831.8
Income (INR, median)	8,415.2	2,862.9	5,520.4	7,128.4	9,023.8	9,569.8	10,999.1
Housing Value (INR, median)	975,000.0	580,000.0	1,088,000.0	1,000,000.0	1,100,000.0	922,200.0	900,000.0
Imputed Mortgage (INR, median)	9,401.4	5,592.7	10,491.0	9,642.5	10,606.8	8,892.3	8,678.3
Unaffordable at Low NHBS (%)	72.0	74.7	78.0	74.9	72.6	70.2	71.0
Unaffordable at Mod. NHBS (%)	84.1	78.9	84.5	85.7	84.4	83.1	84.0
Unaffordable at 30% Rule (%)	86.0	88.6	91.2	90.2	88.2	85.3	83.1

Note: Data are from NSS rounds 58 (2003), 61 (2004), 68 (2012) and 70 (2013). All observations weighted by survey weights. 1.5 × Poverty Headcount ratio is calculated by multiplying the state and region poverty threshold by 1.5 and counting the household below that level of expenditure.

Nevertheless, the results from Table 13 show that renter unaffordability using the residual income approach is 13.7 percent in 2004 and 5.6 percent in 2012. While for owners, the unaffordability using the residual income approach is 73.9 percent in 2003 and 72.0 in 2013. Unaffordability as per the 30 percent rule is similar for owners, but underestimates renter unaffordability as median rent to income ratio has been around one-eighth. For megacities, the estimates are better: 2.6 percent for renters and 76.2 percent for owners in 2012–2013 at the Low NHBS.

TABLE 14: HOUSING AFFORDABILITY ESTIMATES BY URBAN INCOME QUINTILES

	All	Urban Income Quintiles				
		Q1	Q2	Q3	Q4	Q5
Panel A: 2004 Renters						
Unaffordable at Low NHBS	13.7	42.3	31.3	12.1	0.9	0.0
Unaffordable at Moderate NHBS	34.6	65.9	71.4	48.7	10.2	0.1
Unaffordable at 30% Rule	3.0	3.8	4.0	2.9	2.2	2.7
Panel B: 2003 Owners						
Unaffordable at Low NHBS	73.6	96.3	91.3	80.2	60.5	46.0
Unaffordable at Moderate NHBS	86.6	99.2	98.7	94.7	83.4	62.4
Unaffordable at 30% Rule	73.8	71.2	68.8	73.4	73.5	81.2
Panel C: 2003–2004 Total						
Unaffordable at Low NHBS	57.8	81.8	74.4	62.2	44.3	35.0
Unaffordable at Moderate NHBS	72.8	90.3	91.0	82.6	63.5	47.6
Unaffordable at 30% Rule	55.1	53.1	50.5	54.8	54.2	62.5
Panel D: 2012 Renters						
Unaffordable at Low NHBS	3.7	9.3	7.1	1.7	0.1	0.0
Unaffordable at Moderate NHBS	15.7	22.0	35.6	17.8	3.1	0.0
Unaffordable at 30% Rule	5.9	3.8	6.4	7.8	5.2	6.2
Panel E: 2013 Owners						
Unaffordable at Low NHBS	72.0	73.0	79.3	81.7	71.3	58.8
Unaffordable at Moderate NHBS	84.1	90.3	95.4	93.9	84.6	65.5
Unaffordable at 30% Rule	86.0	81.6	82.6	85.4	87.6	88.4
Panel F: 2012–2013 Totals						
Unaffordable at Low NHBS	52.9	55.5	60.1	57.3	51.1	42.8
Unaffordable at Moderate NHBS	64.9	71.6	79.5	70.7	61.5	47.6
Unaffordable at 30% Rule	63.5	60.3	62.3	61.7	64.3	66.0

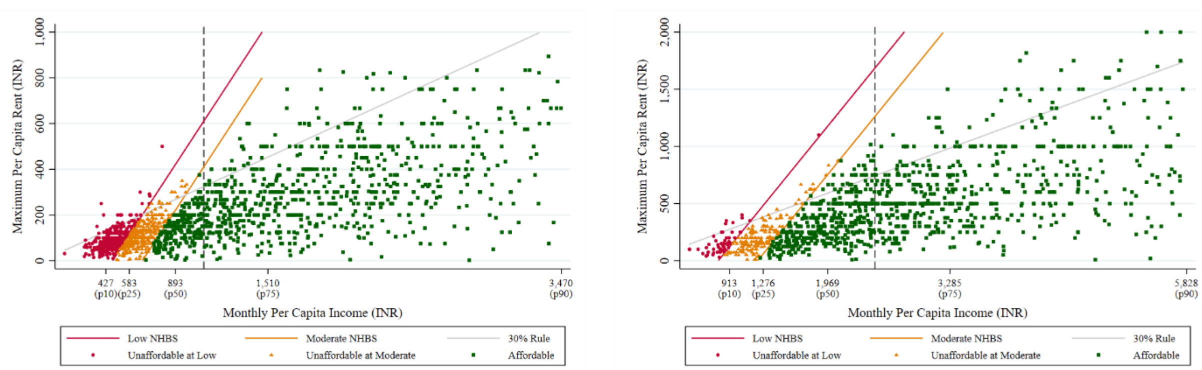
Note: Data are from NSS rounds 58 (2003), 61 (2004), 68 (2012) and 70 (2013). All observations weighted by household survey weights.

An alternative angle to view these affordability results is by income quintile and combining these estimates into a total country urban average. Table 14 shows the housing affordability estimates by quintiles and combined adjacent renter and owner estimates into an urban joint estimate for 2003–2004 and 2012–2013 across renters and owners, including joint estimates by quintile. It is apparent that affordability has improved from 2003–2004 to 2012–2013 across all three metrics: unaffordable at Low NHBS has decreased from 57.8 percent to 52.9 percent and this has been driven by improvements in renter affordability, while the renting share of urban households has remained constant at about a quarter. What is also clear from Table 14 is how the 30 percent rule is not a good measure especially for wealthier households and how it underestimates unaffordability for renters.

A graphical representation of affordability helps characterize the thresholds and the actual data. Figure 3 shows the affordability for Tamil Nadu for 2004 and 2012. Only one state can be presented on a graph, as each state has its own poverty line and therefore each state has its own Low NHBS and Moderate NHBS. For renters, the graphical representation is straightforward on a per capita basis as the poverty line estimates in India are linear with household size. The lines represent the thresholds, and the scatter points represent actual households from the data. Panel B of Figure 3 shows that both Low and Moderate unaffordability has decreased in the state for renters. The representations also show how a 30 percent rule fails to discriminate households sufficiently well.

FIGURE 3: RENTERS AFFORDABILITY IN TAMIL NADU

(A) MAXIMUM RENT, TAMIL NADU 2004 (B) MAXIMUM RENT, TAMIL NADU 2012

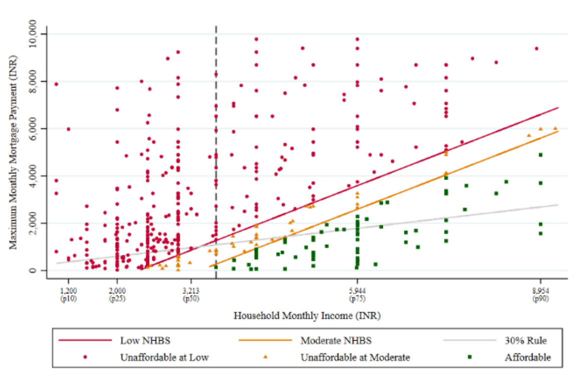


Note: Data from NSS rounds 58 (2004) and 68 (2012). Data weighted by survey weights. Low NHBS corresponds to poverty line and Moderate NHBS corresponds to 1.5 × poverty line. Horizontal dotted line is the median per capita monthly income of renters. X-axis is labeled with nominal urban per capita income percentiles. Unaffordable at Moderate is labeled in a separate color (orange) though calculation for Moderate includes red scatter points.

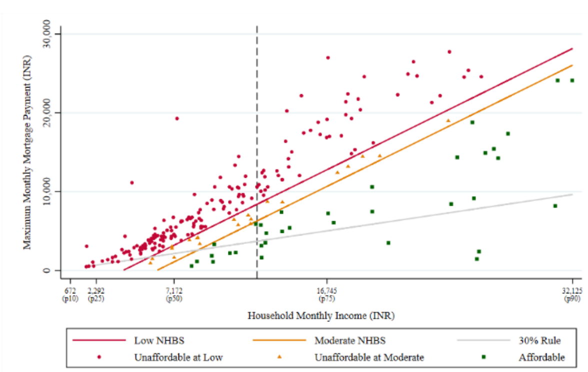
For owners, dividing the monthly mortgage by the household size is less intuitive and most residual income approaches for owners produce graphs by household size. This helps characterize a modal household in terms of their outlay and income (Stone, Burke and Ralston 2011). Mathematically, it is possible to calculate a per capita mortgage payment, but because neither lenders not policy makers use such figures, a household size approach is used here. Such a per capita mortgage construction is possible here as the NHBS is linear in household size. This is not the case in developed countries where the budget standard differs by household size, and therefore each household size would require its own Low and Moderate NHBS. Figure 4 shows the corresponding graphical representation for affordability for an owner occupier household. The selected group is for a five-person household in Tamil Nadu. As with the renters, the Low and Moderate NHBS is state-specific so only a single state can be cleanly represented. The lines in Figure 4 represent the threshold and the scatter represents actual households and where they fall in terms of owner affordability. Given the construction of the residual income approach here using a reverse mortgage and the commensurate increase in real estate prices, many owner households do not have the reported income to be classified as 'affordable'. This is due to several factors including challenges in measuring transitory and permanent income in developing countries, incomplete capital markets, household wealth concentration in illiquid assets such as real estate and a low rental yield which prevents households from releasing liquid income from illiquid real estate. Panels A and B of Figure 4 show that only those households beyond the median household income of all urban renters are classified as 'affordable' using the residual income approach.

FIGURE 4: OWNERS AFFORDABILITY IN TAMIL NADU, HOUSEHOLD SIZE OF FIVE

(A) MAXIMUM MORTGAGE, TAMIL NADU 2004



(B) MAXIMUM MORTAGE, TAMIL NADU 2012



Note: Data from NSS rounds 59 (2005) and 70 (2013). Data weighted by survey weights. Low NHBS corresponds to poverty line and Moderate NHBS corresponds to 1.5 × poverty line. Horizontal dotted line is the median per capita monthly income of renters. X-axis is labeled with nominal urban per capita income percentiles. Unaffordable at Moderate is labeled in a separate color (orange) though calculation for Moderate includes red scatter points. Graph is for household of size 5.

4.7. Residual Income Methodology Extensions

The estimates above for affordability of urban housing in India are made possible by several critical budget standards and capital market assumptions. The literature on housing affordability has focused almost exclusively on urban markets, although there is something to be said about affordability in rural areas. With an unusually large rural population for a lower-middle-income country—just above two-thirds in 2011—thinking about rural housing affordability in India is not trivial. This subsection looks at extending the above affordability methodology for rural homeowners, explores how imputed rents for urban owners differ from using housing valuation, and clarifies the distinction between residual income and residual expenditure estimates for a developing country.

4.7.1. Housing Affordability for Rural Homeowning Households

As of the 2011 census of India, 31.8 percent of the population lived in urban areas. Official population projections show that this is expected to increase to 38.2 percent by 2036, the 2021 estimate is 34.5 percent (National Commission on Population 2020). Therefore, a large percentage—65.5 percent in 2021—of the population is still rural and this is where a larger share of the poverty resides.

The share of rural renters in India is very low. In 2012, the share of renting households was only 2.3 percent in rural areas compared to 27.2 percent in urban areas. Therefore, this section focuses on rural owner occupier households. Further, in developing a rural NHBS, it is not possible to get the actual rent for renters around the rural poverty lines by state. Rather a national average per capita rent for renters is subtracted from the state rural poverty lines to arrive at a Low and Moderate NHBS for rural areas. The simple state averages of these standards that are used are INR 463 and 677 in 2004; and INR 883 and 1,296 in 2012. As expected, these are slightly lower than the urban estimates from Table 12 but are commensurate with the urban estimates.

The median rural housing value in 2005 was INR 50,000 and in 2013 it was INR 180,200. These are four times lower than the median urban estimates from Table 13. Applying the same mortgage assumption as for urban areas to these two years yields unaffordability estimates shown in Table 15.[36] As with urban homeowners, unaffordability estimates are high and much larger than urban counterparts. In 2005, 80.0 of rural homeowners are classified as unaffordable at the Low NHBS, and this decreases to 71.5 percent in 2013. Comparing this to the 30 percent rule shows

[36] This is indeed a stark assumption as the availability of mortgages in rural India is much limited and most dwellings are constructed over time. This section uses a stylized mortgage in order to convert a housing stock to a housing flow for demonstration. It is also feasible to do the same using imputed rents for rural areas.

that the estimates are about the same for 2013 but lower in 2005. So, although housing values are much lower in rural areas, the estimated incomes and lower budget standards do not compensate enough for this to yield a very large increase in estimated affordability.

TABLE 15: HOUSING AFFORDABILITY ESTIMATES FOR RURAL OWNERS IN INDIA

	All	Household Size					
		1	2	3	4	5	6–10
Panel A: 2005 Rural Owners							
Poverty (%)	57.2	30.9	36.0	40.2	46.4	56.7	65.8
1.5 × Poverty (%)	88.0	64.3	75.8	78.1	84.1	88.3	92.0
Expenditure (INR, median)	2,000.0	570.0	1,000.0	1,500.0	1,900.0	2,050.0	2,780.0
Income (INR, median)	2,000.0	570.0	1,000.0	1,500.0	1,900.0	2,050.0	2,780.0
Housing Value (INR, median)	50,000.0	28,000.0	40,000.0	45,000.0	50,000.0	50,650.0	61,000.0
Imputed Mortgage (INR, median)	543.4	304.3	434.7	489.1	543.4	550.5	663.0
Unaffordable at Low NHBS (%)	80.0	73.9	75.7	73.4	75.8	79.5	83.1
Unaffordable at Moderate NHBS (%)	94.4	89.7	90.5	91.6	93.7	94.7	95.4
Unaffordable at 30% Rule (%)	45.0	74.4	65.5	55.1	49.1	44.4	40.1
Panel B: 2013 Rural Owners							
Poverty (%)	45.0	13.6	20.6	26.9	37.2	46.9	55.2
1.5 × Poverty (%)	64.6	26.4	33.5	45.3	60.0	67.8	73.8
Expenditure (INR, median)	4,250.6	2,353.8	3,491.5	4,091.4	4,102.3	4,340.6	5,191.8
Income (INR, median)	4,250.6	2,353.8	3,491.5	4,091.4	4,102.3	4,340.6	5,191.8
Housing Value (INR, median)	180,200.0	100,000.0	145,500.0	175,000.0	188,000.0	180,000.0	212,400.0
Imputed Mortgage (INR, median)	1,737.6	964.3	1,403.0	1,687.4	1,812.8	1,735.7	2,048.1
Unaffordable at Low NHBS (%)	71.5	52.7	51.7	61.5	70.3	72.2	76.7
Unaffordable at Moderate NHBS (%)	81.8	63.9	63.5	74.5	81.3	83.7	85.3
Unaffordable at 30% Rule (%)	71.5	83.7	74.8	74.6	74.3	70.6	69.4

Note: Data are from NSS rounds 58 (2003), 61 (2004), 68 (2012) and 70 (2013). All observations weighted by survey weights.

4.7.2. Using Imputed Rent for Urban Housing Affordability

Many housing expenditure surveys also cover imputed rent for urban homeowners, although this is not used to calculate total expenditure, it is part of the household expenditure global framework. In India, the household budget surveys from NSS rounds 61 (2005) and 68 (2011) collected imputed rent for urban homeowners. The guidelines for field survey staff from the NSS manuals suggest: “imputation will be done on the basis of the prevailing rate of rent for similar accommodation in the locality.” Unlike other housing or wealth surveys, this does not include the input from professional appraisals and is therefore less reliable. In 2005, the median imputed rent for urban homeowners was INR 1,000 with a mean of INR 1,468, while in 2012 the median imputed rent was INR 2,000 and a mean of INR 3,179. These are higher than the rental estimates from the same years and yield a median rent-to-income ratio of about a fifth to a quarter.

For 1993 and 2002 when both imputed rent and square footage of dwellings were collected, the average, median rent and imputed rent to area estimates are similar, suggesting that the imputed rents may not suffer from a valuation bias based on a square foot basis. Using imputed rents for urban homeowners yields 56.5 percent of households as being in unaffordable housing in 2004, and 47.2 percent in 2012 (Table 16). These are lower than the estimates of about three-quarters unaffordability form Table 13, but cannot be used for assessing mortgages for households.

TABLE 16: HOUSING AFFORDABILITY ESTIMATES FOR URBAN OWNERS WITH IMPUTED RENTERS

	All	Household Size					
		1	2	3	4	5	6-10
Panel A: 2004 Urban Owners							
Unaffordable at Low NHBS (%)	56.5	91.5	61.9	57.7	56.2	52.4	55.9
Unaffordable at Moderate NHBS (%)	70.3	94.6	72.2	68.9	68.7	66.7	72.0
Unaffordable at 30% Rule (%)	49.1	95.7	76.1	65.4	57.2	45.7	35.3
Panel B: 2012 Urban Owners							
Unaffordable at Low NHBS (%)	47.2	88.6	52.9	50.5	46.5	44.4	43.2
Unaffordable at Moderate NHBS (%)	63.4	90.9	63.9	62.1	60.7	64.8	62.2
Unaffordable at 30% Rule (%)	48.7	92.8	73.2	63.9	54.8	45.2	32.2

Note: Data are from NSS rounds 58 (2003), 61 (2004), 68 (2012) and 70 (2013) and use imputed rents for urban homeowners. All observations weighted by survey weights.

Estimates from Pakistan using a caloric threshold as the starting budget standard and multiplying this by a 'scaling factor' for non-housing non-food expenses, also use imputed rent for estimating unaffordability for urban homeowners (World Bank 2021). The results in that study find that for all urban residents, a third would be classified as living in unaffordable housing. With the urban imputed rent estimates from Table 16 and the urban renter estimates from Table 13, the India average in 2012 using imputed rents and the Low NHBS is 36.3 percent unaffordable. This is similar to the Pakistan estimate. Ideally, transaction data for current mortgage holders against the budget standards should be used to arrive at more precise estimate of owner affordability across India. It is likely that the estimate for owners is between the imputed rent and imputed mortgage values above.

4.7.3. Comparing Income and Expenditure-Based Affordability Measures

Although income has been harder to estimate in developing countries, there have been some recent strides toward getting better household income estimates (Lakner and Milanovic 2016). For India, a recent study by Chancel and Piketty (2019) estimates income from India, with a particular focus on top incomes. The Chancel and Piketty (2019) approach is used in this paper several times for both 2004 and 2012 data. A critical assumption in Chancel and Piketty (2019) preferred expenditure to income transformation is a no borrowing assumption. Therefore, for cases where reported expenditure is greater than income, the higher of these values (expenditure) is used in the transformation function. Similarly, in the IDHS data from 2005 and 2011 that have both income and expenditure measures for about 50,000 households, the correlation between income and expenditure is 0.45 in both 2005 and 2012. The data do not permit to use the IDHS to arrive at an affordability metric using this income data (as the expenditure data has not been mapped to the poverty line). Nevertheless, the reasonable correlations and the underlying work from Chancel and Piketty (2019) suggest that at the Low and Moderate budget standards the affordability estimates are not very different.

4.8. A Suggested Way Forward for Housing Affordability Estimates for India

The analysis in this section attempts to outline how the residual income approach can be used in a developing country context. First, an NHBS is presented using India's poverty methodology and assumptions about housing outlays around the poverty line. This standard can be used and updated periodically and is independent of the subsequent estimates of affordability for 2004–2005 and 2012–2013. A second important point, as has been noted by others (World Bank 2020), is that the 30 percent rule is not adequate for India. The affordability estimates above for renters have improved as incomes have increased and poverty has decreased. For owners, the NHBS can be used for mortgage affordability assessments prospectively. The owner affordability estimates using actual housing values suggest a high degree of unaffordability which is likely a manifestation of appreciating housing values and homeowners without current mortgages. The imputed rents for owners are difficult to assess given the lack of comparable data points to assess their validity, though reassuringly the affordability estimates for owners using imputed rents in Table 15 are lower than those in Table 13. To improve these estimates for owners, actual transaction data could be used—though this will not yield a population-based estimate, but rather a prospective tool for new mortgage holders.

5. Conclusion

The analysis has demonstrated several important points for housing policy in India. First, and the main result of the paper, is that there is a high income elasticity of demand for housing.

This brings forward the estimates from the 1980s and 1990s into a contemporary context where the demand for housing is likely now elastic. This is grounded in preferences for better water and sanitation amenities as shown by the hedonic pricing regressions and the within-year distributional shares of such amenities. This strongly augurs for more public investment into such services and less public investment to further support demand. It also suggests conceptualization of housing in developing countries squarely in a supply and demand narrative that is more closely connected to health and nutrition, and not simply as a shelter narrative. Since the housing demand estimates here are for renters, they do not suffer from the direct effect of government programs on subsidizing housing ownership or on the high propensity of households in India to save in real estate and other illiquid assets such as gold. Further, the rental data is the most accurate nationwide market data for repeat housing transactions, and renters form one-third of households across urban India.

A second major implication of this analysis is the increasing efficiency of rental markets in India and in megacities. A rental price index constructed in this paper from a hedonic pricing model for 11 megacities closely tracks two other housing price indices from India—one a pure sales index and the other a hybrid index based on both rental and for-sale dwellings. The increasing efficiency of rental markets is also observed through the switching sign and statistical significance of the price term in the demand equations, suggesting the legacy of rent control and other regulations that have hindered the rental market are beginning to wane and rental prices are providing true price signals. This is encouraging and anecdotal evidence suggests that increasing foreign direct investment in the rental market and the recent regulations on REITs do hold promise for the future. This highlights the need for a narrative shift towards greater importance of the role of rental markets as a viable option for emerging markets, where often home ownership unfortunately captures most of the fiscal and policy attention. The modal tenancy act and the new legal framework to protect renters across India is therefore welcome.

The distributional results highlight the need for policy and analysis into housing in urban India to be more attuned to changing preferences and the importance of precise targeting. Although not new to the poverty and social protection literature globally and in India, such income decile cuts should become part of the input toward the definition of the various and overlapping housing income categories of EWS, LIG, MIG, and HIG.

Finally, the exposition of housing affordability in India sheds light on the methodological difficulties in arriving at a simple answer to the question of how affordable housing is in India. The demand estimates suggest that the supply side is where policy should focus more. Nevertheless, based on simple ratios in a global context, housing outlays in urban India are low. However, adopting a reverse claim approach on total expenditure (the residual income methodology) and using a non-housing budget standard suggest that unaffordability may be close to the poverty rate. Specifically, it shows that affordability for renters has improved over time, but less so for owners – both through a stylized mortgage approach and an imputed rent approach. Looking forward, in terms of these affordability results, it will be important to strengthen these owner affordability estimates with transaction data.

The main overarching implications for policy are threefold. Firstly, is to explore any constraints on the supply side given that housing demand is so high. Secondly, to better appreciate rental markets for their increased efficiency as a viable (and not inferior) solution to housing challenges across urban India for some households. Thirdly, to ground income categories and housing types from actual data to improve how housing outcomes are conceptualized, so policy and housing program design can be better calibrated.

References

Ahmad, Sohail, Mack Joong Choi, and Jinsoo Ko. 2013. "Quantitative and Qualitative Demand for Slum and Non-Slum Housing in Delhi: Empirical Evidences from Household Data." *Habitat International* 38: 90–99. https://academic.microsoft.com/paper/2065962154.

Al Obaid, Hussain Mohammed A. 2020. "Factors Determining Housing Demand in Saudi Arabia." *International Journal of Economics and Financial Issues* 10.5: 150–157.

Alatas, Vivi, Abhijit Banerjee, Rema Hanna, Benjamin A Olken, and Julia Tobias. 2012. "Targeting the Poor: Evidence from a Field Experiment in Indonesia." *American Economic Review* 102 (4): 1206–40.

Alok, Aditya, and Pankti Vora. 2011. "Rent Control in India-Obstacles for Urban Reform." *NUJS Law Review* 4: 83–100.

Athaide, Malcolm. 2008. "The Robustness of Residex as a House Price Index." *Available at SSRN 1634620.*

Badarinza, Cristian, Vimal Balasubramaniam, and Tarun Ramadorai. 2016. "The Indian Household Finance Landscape." *SSRN 2797680* (SSRN 2797680).

Bajari, Patrick, and Matthew E. Kahn. 2005. "Estimating Housing Demand with an Application to Explaining Racial Segregation in Cities." *Journal of Business & Economic Statistics* 23.1: 20–33.

Basu, Sreelekha. 1971. "Estimation of Net National Product from Consumer Expenditure Data." *Economic and Political Weekly* 830–832.

Bayer, Patrick, Robert McMillan, and Kim Reuben. 2004. "The Causes and Consequences of Residential Segregation: An Equilibrium Analysis of Neighborhood Sorting." *Working Paper, Yale University.*

Bird, Richard M., and Eric M. Zolt. 2005. "The Limited Role of the Personal Income Tax in Developing Countries." *Journal of Asian Economics* 16.6: 928–946.

Börsch-Supan, Axel, Florian Heiss, and Miki Seko. 2001. "Housing Demand in Germany and Japan." *Journal of Housing Economics* 10.3: 229–252.

Budding, David. 1980. *Housing Deprivation among Enrollees in the Housing Allowance Demand Experiment.* Cambridge, MA.

Census of India. 2011. *Housing Stock, Amenities & Assets in Slums.*

Chancel, Lucas, and Thomas Piketty. 2019. "Indian Income Inequality, 1922-2015: From British Raj to Billionaire Raj?" *Review of Income and Wealth* 65, : S33–S62.

Chen, Jie, and Minzhou Jin. 2014. "Income elasticity of housing demand in China: Micro-data evidence from Shanghai." *Journal of Contemporary China* 23.85: 68–84.

Chen, Jie, Qianjin Hao, and Mark Stephens. 2010. "Assessing Housing Affordability in Post-reform China: A Case Study of Shanghai." *Housing Studies* 25 (6): 877–901. https://academic.microsoft.com/paper/2001838392.

Davies, James B., Rodrigo Lluberas, and Anthony F. Shorrocks. 2017. "Estimating the Level and Distribution of Global Wealth, 2000–2014." *Review of Income and Wealth* 63.4: 731–759.

Davies, James B., Susanna, Shorrocks, Anthony Sandström, and Edward N. Wolff. 2011. "The Level and Distribution of Global Household Wealth." *The Economic Journal* 121 (551): 223–254.

De Leeuw, Frank. 1971. "The Demand for Housing: A Review of Cross-Section Evidence." *The Review of Economics Statistics* 1–10.

Deaton, Angus. 2005. "Measuring Poverty in a Growing World (or Measuring Growth in a Poor World)." *Review of Economics and Statistics* 87.1: 1–19.

Dholakia, Bakul H. 1982. *The Economics of Housing in India.* Mumbai: National Buildings Organisation (India), U.N. Regional Housing Centre for the E.S.C.A.P.

Dolbeare, Cushing N. 1966. "Housing Grants for the Very Poor." Philadelphia Housing Association, Philadelphia.

Engel, Ernst. 1857. "Die Produktions- und Consumtionsverhältnisse des Königreichs Sachsen." *Zeitschrift des Statistischen Büreaus des Königlich Sächischen Ministeriums des Innern. Reprinted in Engel (1895). Appendix I, pp. 1–54* 8 and 9.

Ermisch, John F., Jannette Findlay, and Kenneth Gibb. 1996. "The Price Elasticity of Housing Demand in Britain: issues of Sample Selection." *Journal of Housing Economics* 5.1: 64–86.

Field, Erica, Matthew Levinson, Rohini Pande Pande, and Sujata Visaria. 2008. "Segregation, Rent Control, and Riots: The Economics of Religious Conflict in an Indian City." *American Economic Review* 98 (2): 505–10.

Follain, James, Gill-Chin Lim, and Bertrand Renaud. 1980. "The Demand for Housing in Developing Countries: The Case of Korea." *Journal of Urban Economics* 7.3: 315–336.

Fontenla, Matías, and Fidel Gonzalez. 2009. "Housing Demand in Mexico." *Journal of Housing Economics* 18.1: 1–12.

Fontenla, Matias, Fidel Gonzalez, and Juan Carlos Navarro. 2009. "Determinants of Housing Expenditure in Mexico." *Applied Economics Letters* 16.17: 1731–1734.

Gabriel, Michelle, Keith Jacobs, Kathy Arthurson, Terry Burke, and Judith Yates. 2005. "Conceptualising and Measuring the Housing Affordability Problem." *AHURI Research Paper*. https://academic.microsoft.com/paper/2209229581.

Gallin, Joshua. 2006. "The Long-Run Relationship Between House Prices and Income: Evidence from Local Housing Markets." *Real Estate Economics* 34.: 417–438.

Gan, Quan, and Robert J. Hill. 2009. "Measuring Housing Affordability: Looking Beyond the Median." *Journal of Housing Economics* 18 (2): 115–125. https://academic.microsoft.com/paper/2003457565.

García, Javier A. Barrios, and José E. Rodríguez Hernández. 2008. "Housing Demand in Spain According to Dwelling Type: Microeconometric Evidence." *Regional Science and Urban Economics* 38.4: 363–37.

Ghosh, Ratna. 2018. "Approach to Housing Policy: The Indian Perspective ." *6th Annual International Conference on Architecture and Civil Engineering.*

Glaeser, Edward L., and Joseph Gyourko. 2003. "The Impact of Building Restrictions on Housing Affordability." *Economic Policy Review* 9.2.

Goodman. 1988. "An Econometric Model of Housing Price, Permanent Income, Tenure Choice, and Housing Demand." *Journal of Urban Economics* 23.3: 327–353.

Goodman. 1978. "Hedonic Prices, Price Indices and Housing Markets." *Journal of Urban Economics* 5 (4): 471–48.

Goodman, Allen C., and Masahiro Kawai. 1982. "Permanent Income, Hedonic Prices, and Demand for Housing: New Evidence." *Journal of Urban Economics* 12.2: 214–237.

Government of India. 1993. "Report of the Expert Group on Estimation of Proportion and Number of Poor." Perspective Planning Division, Planning Commission.

Government of India. 2009. "Report of the Expert Group to Review the Methodology for Estimation of Poverty." Planning Commission.

Gyourko, Joseph, and Raven Molloy. 2014. "Regulation and Housing Supply." *Handbook of Regional and Urban Economics* 5: 1289–1337.

Haffner, Marietta E. A., and Harry J. F. M. Boumeester. 2010. "The Affordability of Housing in the Netherlands: An Increasing Income Gap Between Renting and Owning?" *Housing Studies* 25 (6): 799–820. https://academic.microsoft.com/paper/2149847135.

Haffner, Marietta, and Harry Boumeester. 2015. "Housing Affordability in the Netherlands: the Impact of Rent and Energy Costs." *Journal of Housing and The Built Environment* 30 (2): 293–312. https://academic.microsoft.com/paper/2028187226.

Harish, Swastik. 2016. "Public Social Rental Housing in India." *Economic & Political Weekly* 51.5: 49–56.

Hashim, Zainal Abidin. 2010. "House Price and Affordability in Housing in Malaysia." *Akademika* 78 (1). https://academic.microsoft.com/paper/25189649.

Heckman, James J. 1979. "Sample Selection Bias as a Specification Error." *Econometrica: Journal of the Econometric Society* 153–161.

Holly, Sean, Pesaran M. Hashem, and Takashi Yamagata. 2010. "A Spatio-Temporal Model of House Prices in the USA." *Journal of Econometrics* 158.1: 160–173.

Jimenez, Emmanuel, and Douglas H. Keare. 1984. "Housing Consumption and Permanent Income in Developing Countries: Estimates from Panel Data in El Salvador." *Journal of Urban Economics* 15.2: 172–194.

Johri, Mira, Dinesh Chandra, S. V. Subramanian, Marie-Pierre Sylvestre, and Smriti Pahwa. 2014. "MDG 7c for Safe Drinking Water in India: An Illusive Achievement." *Lancet* 383 (9926): 1379.

Kahneman, Daniel, Jack L. Knetsch, and Richard H. Thaler. 1991. "Anomalies: The Endowment Effect, Loss Aversion, and Status Quo Bias." *Journal of Economic Perspectives* 5 (1): 193–206. https://academic.microsoft.com/paper/2165893637.

Kumar, Arjun. 2016. "India's Residential Rental Housing." *Economic & Political Weekly* 51.24: 112–120.

Kutty, Nandinee K. 2005. "A New Measure of Housing Affordability: Estimates and Analytical Results." *Housing Policy Debate* 16.1: 113–142.

Lakner, Christoph, and Branko Milanovic. 2016. "Global Income Distribution: From the Fall of the Berlin Wall to the Great Recession." *The World Bank Economic Review* 30.2: 203–232.

Lee, Tong Hun. 1968. "Housing and Permanent Income: Tests Based on a Three-Year Reinterview Survey." *The Review of Economics and Statistics* 480–490.

Linneman, Peter D., and Isaac F Megbolugbe. 1992. "Housing Affordability: Myth or Reality?" *Urban studies* 29.3-4: 369–392.

Lodhi, Akhtar, and Hafiz A. Pasha. 1991. "Housing demand in developing countries: a case-study of Karachi in Pakistan." *Urban Studies* 28.4: 623-634.

Lodhi, Akhtar, and Hafiz A. Pasha. 1991. "Housing Demand in Developing Countries: A Case-Study of Karachi in Pakistan." *Urban Studies* 28.4: 623–634.

Lowry, Ira South. 1971. *Housing Assistance for Low-Income Urban Families: a Fresh Approach.* New York City Rand Institute.

Lozano, N., and C. Young. 2014. "Housing Demand in Urban Africa." *World Bank Unpublished paper.*

Malpezzi, Stephen. 1999. "Economic Analysis of Housing Markets in Developing and Transition Economies." *Handbook of regional and urban economics* 3: 1791–1864.

Malpezzi, Stephen, and Stephen Mayo. 1987. "The Demand for Housing in Developing Countries: Empirical Estimates from Household Data." *Economic Development and Cultural Change* 35.4: 687–721.

Malpezzi, Stephen, and Vinod K. Tewari. 1991. "Cost and Benefits of Residential Rent Control in Bangalore, India." *Mimeo, World Bank.*

Mayo, Stephen K. 1981. "Theory and Estimation in the Economics of Housing Demand." *Journal of Urban Economics* 10.1: 95–116.

Mayo, Stephen K, Stephen Malpezzi, and David J. Gross. 1986. "Shelter Strategies for the Urban Poor in Developing Countries." *World Bank Research Observer 1.2* 1 (2): 183–203. https://academic.microsoft.com/paper/1964150233.

McKinsey Global Institute. 2014. "A Blueprint for Addressing the Global Affordable Housing Challenge."

Mehta, Meera, and Dinesh Mehta. 1987. "Metropolitan Housing Markets: A Case Study of Ahmedabad." *Economic and Political Weekly* 22 (40): 1701–1709.

Millennial Housing Commission. 2002. "Meeting Our Nation’s Housing Challenges - A Report of the Bipartisan Millennial Housing Commission Appointed by the Congress of the United States."

Milligan, Vivienne Rae. 2003. "How Different? Comparing Housing Policies and Housing Affordability Consequences for Low Income Households in Australia and the Netherlands." https://academic.microsoft.com/paper/1486362604.

Moore, Eric, and Andrejs Skaburskis. 2004. "Canada's Increasing Housing Affordability Burdens." *Housing Studies* 19 (3): 395–413. https://academic.microsoft.com/paper/2012574215.

National Commission on Population. 2020. "Population Projections for India and States 2011 - 2036." Report of the Technical Group on Population Projections.

National Housing Bank. 2008. *A Study of Residential Demand in India.* Monograph, New Delhi and Pune: National Housing Bank - National Institute of Bank Management.

Newman, Dorothy K. 1971. "Housing the Poor and the Shelter to Income Ratio." *US Congress, House Committee on Banking and Currency. Papers Submitted to Subcommittee on Housing Panels. 92nd Congress, First Session.*

Office of the Registrar General & Census Commissioner India. 2011. "Census of India 2011 - Meta Data."

Pınar, Abuzer, and Murat Demir. 2016. "The Impact of Social Housing Program on the Demand for Housing in Turkey: A Cross-Section Analysis." *Applied Economics and Finance* 3.4: 20–28.

Quigley, John M., and Steven Raphael. 2004. "Is Housing Unaffordable? Why Isn't It More Affordable?" *Journal of Economic Perspectives* 18 (1): 191–214.

Rapkin, Chester. 1957. "Rent-income Ratio--Should Formula for Public Housing be Changed?." *Journal of Housing* 14(1): 8–12.

Reserve Bank of India. 2017. "Report of the Housing Finance Committee - Indian Household Finance."

Rouwendal, Jan, and Erik Meijer. 2001. "Preferences for Housing, Jobs, and Commuting: A Mixed Logit Analysis." *Journal of Regional Science* 41.3: 475–505.

Saiz, Albert. 2010. "The Geographic Determinants of Housing Supply." *Quarterly Journal of Economics* 125 (3): 1253–1296.

Schwabe, Hermann. 1868. "Das Verhaltniss von Miethe und Einkom-men in Berlin." *Berlin und seine Entwickelung fur 1868* 264–67.

Sengupta, Urmi, and Allan G. Tipple. 2007. "The Performance of Public-Sector Housing in Kolkata, India, in the Post-Reform Milieu." *Urban Studies* 44.10: 2009–2027.

Singh. 2015. "Housing Price Indices in India." *IIM Bangalore Research Paper* (477).

—. 2014. *Quotidian Urban Challenges: Development, Environment and Health.* New Delhi: YS Books International.

Skoufias, Emmanuel, Benjamin Davis, and Sergio De La Vega. 2001. "Targeting the Poor in Mexico: An Evaluation of the Selection of Households into PROGRESA." *World Development* 29 (10): 1769–1784.

Solak, Ali Osman, and Burhan Kabadayi. 2016. "An Econometric Analysis of Housing Demand in Turkey." *Advances in Management and Applied Economics* 6.3: 47–57.

Stone, Michael. 2006. "A Housing Affordability Standard for the UK." *Housing Studies* 21 (4): 453–476. https://academic.microsoft.com/paper/2171372685.

Stone, Michael. 1975. "The Housing Crisis, Mortgage Lending and Class Struggle." *Antipode* 7 (2): 22–37. https://academic.microsoft.com/paper/2026725252.

Stone, Michael. 2006. "What is Housing Affordability? The Case for the Residual Income Approach." *Housing Policy Debate* 17 (1): 151–184. https://academic.microsoft.com/paper/2153943820.

Stone, Michael, Terry Burke, and Liss Ralston. 2011. "The Residual Income Approach to Housing Affordability: The Theory and the Practice." *AHURI Positioning Paper* (139). https://academic.microsoft.com/paper/2170663931.

Suhaida, M. S., N. M. Tawil, N. Hamzah, A. I. Che-Ani, and M.M. Tahir. 2010. "Conceptual Overview of Housing Affordability in Selangor, Malaysia." *International Journal of Architectural and Environmental Engineering* 4 (12): 2289–2291. https://academic.microsoft.com/paper/2887995230.

Swaminathan, Madhura. 2010. "The new poverty line: a methodology deeply flawed." *Indian Journal of Human Development* 4 (1): 121–125.

Tandel, Vaidehi, Shirish Patel, Sahil Gandhi, Abhay Pethe, and Kabir Agarwal. 2016. "Decline of Rental Housing in India: The Case of Mumbai." *Environment and Urbanization* 28 (1): 259–274.

Tandoh, Francis, and Devi Datt Tewari. 2016. "The Income and Price Elasticity of Demand for Housing in Ghana: Empirical Evidence from Household Level Data." *South African Journal of Economic and Management Sciences* 19.2: 160–174.

Tewari, Vinod K, and Krishna T. Kumar. 1986. *Rent control in India: its economic effects and implementation in Bangalore.* Water Supply and Urban Development Department, Operations Policy Staff, World Bank.

Tiwari, Piyush, and Jyoti Parikh. 1998. "Affordability, Housing Demand and Housing Policy in Urban India." *Urban Studies* 35 (11): 2111–2129. https://academic.microsoft.com/paper/2139970372.

Tiwari, Piyush, Kirit Parikh, and Jyoti Parikh. 1999. "Effective Housing Demand in Mumbai (Bombay) Metropolitan Region." *Urban Studies* 36.10: 1783–1809.

UN-Habitat. 1996. *The Habitat Agenda Goals and Principles, Commitments and the Global Plan of Action.* Istanbul: UN-Habitat.

Wadhwa, Kiran. 1988. "Housing Programmes for Urban Poor: Shifting Priorities." *Economic and Political Weekly* 1762–1767.

Wood, Gavin, Rachel Ong, and Melek Cigdem. 2014. "Housing Affordability Dynamics: New Insights from the Last Decade." *AHURI Final Report* (233). https://academic.microsoft.com/paper/2100255919.

World Bank. 2021. "Applying the Residual Expenditure Methodology in Urban Pakistan."

—. 2020. "Measuring Housing Affordability, Literature Review and Recommendations: Refining approaches used by the World Bank Group." *Working Paper.*

World Health Organization. 2019. "Progress on Household Drinking Water, Sanitation and Hygiene 2000–2017: Special Focus on Inequalities." World Health Organization.

Yang, Zan, and Jie Chen. 2014. *Housing Affordability and Housing Policy in Urban China.* https://academic.microsoft.com/paper/2503492041.

Yates, Judith, and Michelle Gabriel. 2006. "Housing Affordability in Australia." *AHURI Research Paper.* https://academic.microsoft.com/paper/2112440876.

Yates, Judith, and Vivienne Milligan. 2007. "Housing Affordability: A 21st Century Problem." *AHURI Final Report* (105). https://academic.microsoft.com/paper/2168769799.

Zabel, Jeffrey E. 2004. "The Demand for Housing Services." *Journal of Housing Economics* 13.1: 16–35.

Zhang, Hong, Shaokai Li, and Yanhu Kong. 2016. "Elasticity of Demand for Urban Housing in Western China Based on Micro-data - A Case Study of Kunming." *The Journal of Industrial Distribution & Business* 7.3.

Zheng, Xian, Yu Xia, Eddie CM Hui, and Linzi Zheng. 2018. "Urban Housing Demand, Permanent Income and Uncertainty: Microdata Analysis of Hong Kong's Rental Market." *Habitat International* 74: 9–17.

Annex I: K-Modes Clustering of Urban Housing (2018)

To demonstrate how classification tools can better help understand the multidimensional amenities of housing in India, this annex undertakes a K-modes clustering exercise using machine guided learning tools to classify urban households into six categories. K-modes was selected over K-means as several housing amenities are either present or absent and the mean of such indicator variables has little meaning in the housing context. The accuracy between the K-modes and the K-means method is 78 percent. Using the elbow-method, six clusters were selected. The results of the clustering and a description of each cluster is presented below in ascending order of housing quality and median rent.

K-MODES CLUSTER OF URBAN RENTAL HOUSING IN INDIA (2018)

Cluster Name	Share of Urban Households (%)	Roof Material	With Separate Kitchen	Number of Rooms	Drinking Water Source	Sanitation Facility	Median Rent (INR)	Median Consumer Expenditure (INR)
Small House without Separate Kitchen, Limited Access to Water or Sanitation Services	9.30	Permanent	No	1	Pump Outside Dwelling	Flush	1,200	6,800
Small House without Separate Kitchen, Limited Access to Water Service	6.35	Metal	No	2	Piped into Yard	Flush	1,500	8,057
Small House with Limited Access to Water Service.	14.32	Permanent	Yes	3	Piped into Dwelling	Flush	2,113	10,000
Large House with Limited Access to Water Service	32.84	Permanent	Yes	5	Pump into Dwelling	Flush	3,000	12,100
High Quality House with Access to Improved Water and Sanitation Service	26.82	Permanent	Yes	4	Piped into Dwelling	Flush	3,000	12,300
High Quality Large House with Access to Improved Water and Sanitation Service	10.38	Permanent	Yes	>6	Piped into Dwelling	Flush	5,000	16,800

Note: Data are from NSS rounds 76 (2018). Permanent roof is tiles, slate, burnt brick, stone, limestone, iron, zinc, other metal sheet, asbestos sheet, cement, or reinforced concrete.

Annex II: Rents across the Income Distribution for 2018 (Table 11)

RENTS AND BY INCOME DECILE, URBAN INDIA 2018

	Total	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Panel A: Urban India											
Rent (INR, median)	1,000.0	1,500.0	2,000.0	2,500.0	2,600.0	3,000.0	3,500.0	4,000.0	5,000.0	7,000.0	2,500.0
Area (sq ft, median)	143.0	180.0	220.0	260.0	280.0	310.0	340.0	380.0	444.0	520.0	280.0
Rent per sq ft (INR, median)	6.1	8.1	8.6	8.8	9.0	9.5	10.4	10.7	10.7	13.6	9.1
Rent to Monthly Income (%, median)	25.6	30.0	28.6	27.1	25.6	24.8	22.3	20.4	17.8	19.1	24.7
Panel B: Megacities											
Rent (INR, median)	1,200.0	2,000.0	3,000.0	3,200.0	4,000.0	4,500.0	5,000.0	5,000.0	7,800.0	9,000.0	3,000.0
Area (sq ft, median)	145.0	172.0	200.0	275.0	260.0	300.0	340.0	420.0	500.0	490.0	255.0
Rent per sq ft (INR, median)	7.2	11.5	13.2	11.7	13.8	13.9	15.3	15.0	15.3	18.9	13.2
Rent to Monthly Income (%, median)	28.9	31.3	30.0	28.6	26.1	24.6	23.6	21.1	23.5	20.9	26.4

Note: Data are from NSS round 76 (2018) All means and medians are weighted by household survey weights.