The Pink Tax: Gender Norms and Rental Housing for Single Women in India

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Abstract

We document a novel gender "pink tax" in shared rental housing markets in India. Using online listings covering more than 230 cities, we find that accommodation advertised for women is priced 6–8% higher than comparable accommodation advertised for men, conditional on detailed housing attributes, amenities, and granular location fixed effects. Similar positive gaps appear in listings from Bangladesh and Sri Lanka, and in household survey data on actual rents in India. A decomposition based on within-building comparisons attributes half of the gap to supply-side costs of renting to women and the remaining to demand-side sorting. The within-building gap is concentrated among small operators and becomes insignificant among large professional providers, a pattern consistent with reputational costs induced by gender norms. On the demand side, women's sorting into safer and higher-amenity neighborhoods also appears to be shaped by conservative gender norms. Combining city-level variation in rents with measures of ancestral and contemporary social norms, we show that the gap is larger where gender norms are more restrictive, including where attitudes toward pre-marital sex are stricter and where men historically played a greater role in productive tasks. Our findings highlight rental housing as an overlooked barrier to single women's economic mobility and labor force participation in rapidly urbanizing economies.

Keywords: Housing. Gender gaps. Digital platforms. India.
JEL: J16, O18, R21, R31, Z13

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1 Introduction

Improving the labor force participation of women is a major policy issue in many developing countries. Urban labor markets offer women opportunities, but accessing these jobs requires access to affordable housing. For married women, housing is frequently bundled with household formation whereas single women must rely on the market for housing. If comparable accommodation is more expensive for women than for men, housing prices for women include a "pink tax" and constitute a direct gender-specific barrier to urban employment. A large literature documents many constraints to female labor force participation, including the gender wage gap, caregiving responsibilities, social norms, safety concerns, women's agency, and workplace amenities (see Heath *et al.* (2025) and Jayachandran (2021) for recent surveys). But evidence on a pink tax in the rental housing markets of developing-country cities remains scarce.

The gender pink tax can act as a potential brake on the broader transition of women into urban labor force. Single women have historically led women's entry into paid work. In the early twentieth century, 40–50% of single women in the United States and over 60% in the United Kingdom were employed, compared with fewer than 10% of married women (Costa, 2000). The participation gap narrowed only as married women entered the labor market in large numbers from the 1950s onward (Goldin, 2006, 2014). Rural–urban migration in India is increasingly female and increasingly economic rather than marital (Kone *et al.*, 2017), yet urban India lags in this transition. Though the age at marriage has risen sharply,[1] labor force participation among single women remains low and similar to that of married women.[2] In conservative social settings, unmarried women face stronger expectations regarding safety and respectability, and history shows that dedicated housing arrangements have been essential to making their city life feasible. The Waltham–Lowell boardinghouse system in the early nineteenth-century United States (National Park Service, 2023; Dublin, 1979) and widespread female factory dormitories in China (Chang, 2009) and Bangladesh served this function.[3] For countries where female labor force participation remains persistently low, such as India and several Middle Eastern economies, removing housing barrier to single women's entry into the labor market could jump-start broader participation transitions and reduce significant economic costs (Hsieh *et al.*, 2019; Ashraf *et al.*, 2022; Bandiera *et al.*, 2022; Goldberg *et al.*, 2025).

This paper uses a novel dataset of shared-housing rental advertisements from more than 230 Indian cities to estimate the gender pink tax and trace its sources to amenities, landlord behavior, and social norms. We study paying guest (PG) housing which is

[1] According to the National Family Life Survey (NFHS), it has risen nationally from 19.8 years in 2005/6 to 22.2 years in 2022/23. The median age at marriage in urban areas is higher—24.3 years in 2022/23.

[2] The participation rate for both stands around 25% (UNFPA, 2025).

[3] O'Henry described the poor housing condition of young working women in New York city in his famous short story "Brickdust Row". A quote from the story: *"If you could see the place where I live you wouldn't ask that. I live in Brickdust Row. They call it that because there's red dust from the bricks crumbling over everything. I've lived there for more than four years. There's no place to receive company. You can't have anybody come to your room. What else is there to do? A girl has got to meet the men, hasn't she?" –Brickdust Row, published in 1907.*

the de facto dormitory sector of urban India. In this segment of the market, beds and rooms rented individually to students and young working migrants, typically in gender-segregated facilities. Gender-targeted listings are legal and common as roughly two-thirds of PG advertisements state an explicit tenant-gender preference.[4] We assemble what is, to our knowledge, the most comprehensive dataset on this market. Our dataset covers majority of PG listings from India's two largest property platforms between 2021 and 2024, comprising more than 100,000 gendered advertisements across more than 230 cities, with detailed information on room, amenity, and building characteristics and geocoded locations. We complement these listings with actual rent payments from a nationally representative household expenditure survey (HCES 2023–24), neighborhood safety audits, parallel listing data from Bangladesh and Sri Lanka, and measures of ancestral and contemporary gender norms.

To understand why a gender gap in rents may exist and where it comes from, we develop a simple model in the tradition of Alonso-Mills-Muth and Roback (1982). In a paternalistic society, women's identities are often tied to their marital status, and they are held to stricter standards of respectability (Jayachandran, 2021, 2015). Our model combines two simple ideas. On the demand side, women place greater value on neighborhood and housing safety either because of intrinsic preference or because social norms impose higher penalties for unsafe or socially disapproved living arrangements. On the supply side, landlords may perceive additional costs when renting to women, including reputational concerns and normative pressures in conservative communities. Together, these mechanisms predict three outcomes: women sort into safer, higher-amenity locations; pay higher rents for comparable units; and consume less housing space. The model predicts that rent differences persist within the same building due to the gender-specific costs expected by landlords, and segments of the market subject to higher burden of norms would display higher gender gap in rents.

The empirical analysis produces three novel and robust findings. First, using the PG listing data, we find that shared accommodations for women are listed at rents that are 6–8% higher than comparable accommodations for men, after controlling for rich housing attributes, amenities, and highly granular location fixed effects. This gap is robust to selection concerns and appears in additional evidence from similar South Asian contexts (Bangladesh and Sri Lanka).[5] Using household survey data on actual rental payments in India, we document that single women pay a 3–4% premium on rental housing compared to men in a market segment which is poorer than that in our listing data.

Second, guided by the model, we decompose the gap into preference heterogeneity on the demand side and additional costs of renting to women on the supply side by estimating the gender gap for comparable residences within the same building. This within-building gap, which approximates the supply-side cost of renting to women, remains large: about [51-56%] of the within-city gender gap. Between-building

[4] In the US, the Federal Fair Housing Act bans gender discrimination in almost all housing arrangements. A rental listing may only express gender preference if a renter is seeking a roommate.

[5] Following the methodology proposed by Oster (2019), we find that selection on unobservables would have to be implausibly high, 11–14 times the selection on observables to explain away this gap.

variation, which mostly captures preference heterogeneity, accounts for the remaining part.

Third, heterogeneity patterns point to the role of social norms. The within-building gap is concentrated among small, locally embedded providers and largely disappears among large professional operators, suggesting that reputational constraints are stronger when landlords are more socially rooted into their neighborhoods. The gender gap among landlords who rent to both men and women is still substantial (6.6%) suggesting that gender gap in rent is induced mostly by social norms instead of gendered preference. On the demand side, larger gaps among students relative to working women are consistent with family-mediated norm pressures in housing choice. City-level variation in contemporary and ancestral norm proxies further supports the view that stricter gender norms are associated with larger rental premia for women.

The paper contributes to three strands of literature. First, we provide what is, to our knowledge, the first evidence that a gender rent premium survives like-for-like comparisons of housing units and the first evidence locating a substantial share of that premium on the supply side. The study by (Harten, 2021) is closest to our analysis. It shows that single women in Shanghai pay nearly 10 percent more for shared housing, but attributes the premium to women's demand for better and safer units as the gap disappears with controls for quality. Our within-building estimates show that, in India, a large share of the premium remains after quality and location are held fixed. The evidence by operator-size and dual-gender-landlord results identify mechanisms that had not been explored before.

Second, we extend the literature on group-based price differentials in housing in a context where discrimination is legal and openly priced. Existing work, largely from developed countries, documents price differentials associated with race and immigration status, as well as discrimination in access to housing using audit and correspondence methods (Ihlanfeldt and Mayock, 2009; Hanson and Hawley, 2011, 2014; Bosch *et al.*, 2010; Ewens *et al.*, 2014; Edelman *et al.*, 2017; Bertrand and Duflo, 2017). Related evidence from the U.S. housing sales market, where gender discrimination is prohibited by law, shows that single men earn higher unlevered housing returns than single women, as a result of differences in listing and negotiation behavior shaped by social attitudes (Goldsmith-Pinkham and Shue, 2023). In India, Datta and Pathania (2016) show that members of marginalized communities are less likely to be recontacted in response to housing applications, indicating discriminatory behavior. While audit and correspondence studies help to detect discriminatory behavior, explicitly gendered listings allow us to observe how that is reflected in rents, and heterogeneity across landlord and tenant types help us to distinguish among taste-based, statistical, and cost-based models of discrimination (Becker, 1957; Arrow, 1973; Phelps, 1972). The evidence favors a norms-induced preference and cost wedges. Specifically, the reputational cost on the supply side behaves like statistical discrimination due to tenant risk but originates in gendered social norms.

Third, we contribute to the literature on gender norms and female economic participation. Gender norms, manifested in restrictions on women's mobility and social interactions, the primacy of men as breadwinners, and the assignment of caregiving responsibilities to women, are strongly associated with lower female participation in work, politics, and entrepreneurship (Cortés *et al.*, 2023; Jayachandran, 2015; Fortin, 2005; Muñoz Boudet *et al.*, 2013; Alesina *et al.*, 2013; Giuliano and Nunn, 2021). A rich body of work also links low female employment to norms rooted in pre-industrial production (Alesina *et al.*, 2013; Carranza, 2014; Hansen *et al.*, 2015) and documents how safety and mobility constraints shape women's schooling, commuting, and job choices in India (Borker, 2020; Chen *et al.*, 2024; Amaral *et al.*, 2025; Kondylis *et al.*, 2025; Garlick *et al.*, 2025). We identify the housing market as a distinct and quantitatively meaningful channel through which norms tax female employment: norms raise housing cost for a single woman before she can supply labor in a city. We also provide rare price-based evidence on norms operating on the supply side of a market — landlords pricing expected social sanction — which complements evidence on gendered targeting in job advertisements (Kuhn and Shen, 2023; Ningrum *et al.*, 2020; Delgado Helleseter *et al.*, 2020; Chaturvedi *et al.*, 2024) .

Our analysis brings new policy insights on accelerating women's entry into urban labor markets in developing countries. India's paying-guest sector is the modern counterpart of boarding house systems observed historically in developed countries, and our results identify potentially addressable frictions within it. Changes in social norms are needed to reduce the burden of respectability on women's choices and lower the female-specific costs faced by landlords. Because the gender premium disappears among large professional operators, policies that reduce the reputational exposure of small landlords or accelerate the professionalization of the affordable segment are more likely to address the tax at its source.

The rest of the paper proceeds as follows. Section 2 describes the gendered paying guest housing market in India. Section 3 develops the conceptual framework. Section 4 outlines the data sources, and Section 5 presents the empirical strategy and results. Section 6 provides supporting evidence on the role of social norms, and Section 7 concludes.

2 "Paying Guest" housing in India and beyond

City populations in developing countries are growing fast, with migration from rural areas playing an important role. For instance, migrants comprised over 40% of the population in the largest Indian cities in 2011.[6] A surging urban population has resulted in around 60% of households residing in rented accommodations.[7] This influx of migrants seeking educational and employment opportunities in metropolitan areas has raised the demand for affordable rental housing.

In much of the South Asian subcontinent, rental accommodation largely takes three forms: single family rentals, shared apartments, and "paying guest" accommodation. The former two are similar to apartment rentals in developed countries wherein a

[6] In-migrants account for 46% of the population in Bengaluru, 44% in Mumbai, and 41% in Delhi (Census of India, 2011).

[7] Approximately 59% of the households in Delhi and Bangalore rent their dwellings (Census of India, 2011).

family or group of individuals may come together to sign a lease with a landlord. However, students and working professionals migrating to cities often do not know others to co-sign a lease with. The rental market for these budget-constrained students and professionals is catered to by landlords who take in "paying guests" and rent out largely gender-segregated, shared accommodation by the bed or room.

Paying guest (PG) shared accommodations are commonly advertised on major real estate platforms and represent a large and growing segment of the rental market in India. In a typical PG arrangement, a landlord rents out individual beds within a room, usually accommodating up to five tenants per room.[8] PG accommodations function as de facto hostels for students and working professionals, often with explicit preferences for one or the other group.

Despite their significance, there is no formal data on the quantity, prices, or attributes of PG accommodation. Anecdotal evidence suggests that landlords often bypass formal registration of rental agreements to avoid paying the government's registration fee, making it difficult to quantify their prevalence.[9]

Double Occupancy PG

Triple Occupancy PG

Figure 1: Paying Guest Accommodations

These shared and mostly gender-segregated accommodations are prevalent not only in India but also in other regions of South and Southeast Asia, including Bangladesh, Pakistan, Sri Lanka, and China. Over 65% of advertisements for PG accommodations specify gender restrictions for tenants.[10] This gender segregation can be attributed to two primary factors: homophily and cultural norms. First, women (men) often prefer to live with other women (men), a preference observed globally. In South Asia, there is an additional layer of cultural norms that discourage cohabitation with members of the

[8]Rooms are largely rented out on single or double occupancy basis (38% each). Triple (13%) and quadruple (5%) occupancy make up a smaller but notable share of the market.

[9]The rental agreement registration fee typically ranges from 0.25% to 2% of the rental value across major cities.

[10]Authors' own calculations based on data from multiple large realty platforms in India.

opposite sex before marriage. Consequently, as young migrants move to urban areas, they tend to seek housing arrangements that align with these social expectations.

The term "paying guest" originates in the practice of renting a spare room within a family home, and this still accounts for a fraction of PG supply. The practice now extends to landlords that operate one or a few PGs as small hostels or boarding houses (with or without board). More recently the market has seen an expansion in large corporate operators that own and manage PGs across multiple cities. The latter include companies such as Zolostays (launched in 2015), Stanza Living (2017) and HelloWorld (2019), which initially focused on students but have expanded to provide fully-furnished rentals to both students and professionals.

Married and cohabiting single women access housing through their spouses, and single women living with family through their parents. Single women with children living independently are also rare in developing countries, including India. We therefore focus on the PG segment of the market to quantify the extent and sources of the gender gap in rents. This segment is disproportionately important for relatively poor migrant students and unattached workers, and focusing on single unattached individuals sidesteps the family-care considerations that influence both labor force participation and housing arrangements.

3 Conceptual Framework

To guide the empirical analysis on the extent and source of gender gap in house rents in urban setting, we develop a simple model building on the models by Alonso (1964), Mills (1967), Muth (1969), and Roback (1982). The model focuses on how social norms shape preference and sorting on the demand side, and gender-specific cost of housing provision on the supply side in this market. The model is described in detail in the appendix. This section presents the intuition of the model and the key results that guide the empirical identification of the different sources of the gender gap in rents.

The model rests on four intuitions. First, social norms raise women's preference for safety: because women are held to stricter standards of respectability, unsafe locations are costlier for them, and they sort into safer and hence more expensive neighborhoods even though they value other amenities exactly as men do. Second, landlords face a gender-specific cost when renting to women, driven by reputational risk and gender attitudes. Because this cost does not vary with the level of rents, its burden relative to rent is heavy in cheap neighborhoods and light in expensive ones, so the relative supply of female PGs is thin in cheap areas and rises with neighborhood quality. This pattern reflects the landlords' cost, not women's tastes. Third, the two mechanisms operate at different spatial levels: sorting moves women across neighborhoods and buildings, while the gender-specific cost follows women into any given building. The part of the gender rent gap that survives building fixed effects therefore reflects the landlords' cost. The part that disappears reflects sorting. Fourth, the burden of gender norms varies across different groups of landlords (large vs small) and women (student vs. working), with higher burden implying larger gender gaps. This allows us to highlight role of social norms driving gender gap on both demand and supply sides. The rest of this section formalizes these statements.

3.1 Basic set-up

We model a city with neighborhoods $j = 1, \ldots, J$ and building/unit types $k = 1, \ldots, K$. Each neighborhood has exogenous safety S_j and a neutral amenity A_j. Individuals belong to gender groups $g \in \{w, m\}$ (women and men), where women have a higher preference for safety ($\theta_w > \theta_m$), but both genders equally value the general amenity A_j with preference parameter β. The difference in preference parameters for safety ($\theta_w > \theta_m$) reflects the fact that social norms dictates women maintain higher standard of respectability than men. An individual of gender g choosing neighborhood–building pair (j, k) has utility

$$U_{igjk} = C_g + \alpha \ln H_{jk} + \theta_g(S_j + T_{jk}) + \beta A_j + \varepsilon_{igjk}, \tag{1}$$

with budget constraint $Y_g = C_g + r_{jk}H_{jk}$. C_g is consumption, T_{jk} is landlord-provided safety abatement (locks, cameras, gated access). r_{jk} is rent/space/sq feet for house type k in neighborhood j and H_{jk} is the housing space (square footage). ϵ_{igj} is an idiosyncratic preference shock following a Type I Extreme Value (Gumbel) distribution. The share of individuals of group g that chooses house type k in neighborhood j is given by the Logit formula:

$$P_{gjk} = \frac{\exp(V_{gjk})}{\sum_{j'=1}^{J} \sum_{k'=1}^{K} \exp(V_{gj'k'})} \tag{2}$$

On the supply side, landlords offer a menu of house types k in neighborhood j. We introduce a compensating differential to represent a friction landlords face when supplying housing to females. This could arise because landlords may fear incurring a "reputation cost" that renting out to women may lead to future losses if women behave in ways that are socially unacceptable. Social norms can also induce animus in terms a psychological cost to renting to women by landlords. Let ψ_g be this per-square-foot cost markup, where $\psi_w = \psi > 0$ and $\psi_m = 0$. The landlord's profit function is:

$$\pi = (r(S_j, A_j, T_{jk}) - \psi_g)H_{jk} - P_j H_{jk} - C(T_{jk}) \tag{3}$$

where P_j is the price of floor space in square meter, and $C(T_{jk}) = \gamma T_{jk}^2/2$ is the cost of abatement. The landlord sets the marginal cost of abatement equal to the marginal willingness to pay of the target resident group. For the house type targeted at group g, the optimal abatement technology is:

$$T_g^* = \frac{\theta_g}{\gamma}. \tag{4}$$

Hence women-targeted units receive higher safety technology when $\theta_w > \theta_m$: landlords install exactly as much safety as the target group is willing to pay for, so provision is a pricing decision rather than a courtesy.[11]

[11] If we allow abatement cost to depend on neighborhood level safety, then the model will predict optimal safety to vary with average neighborhood safety. If abatement cost increases with neighborhood safety, then landlords will provide less T^* in safer neighborhoods. We abstract from this possibility for simplicity.

Using the pricing condition and housing demand, equilibrium rent and housing space for group g in neighborhood j can be written as[12]

$$r_g^*(S_j, A_j) = \big(r_0(S_j, A_j) + \psi_g\big)\,\frac{\alpha\gamma}{\alpha\gamma - \theta_g^2}, \tag{5}$$

$$H_g^*(S_j, A_j) = \frac{\alpha\gamma - \theta_g^2}{\gamma\big(r_0(S_j, A_j) + \psi_g\big)}. \tag{6}$$

where $r_0(S_j, A_j)$ is the base competitive neighborhood rent. Since $\theta_w > \theta_m$ and $\psi_w > 0$, women consume strictly smaller floor space ($H_w^* < H_m^*$) and pay higher rent ($r_w^* > r_m^*$). The two forces compound: women's higher valuation of safety is capitalized into the rent of the units they choose, and landlords pass the gender-specific cost through to the price per square foot. Facing a higher price, women respond by economizing on space.

Equilibrium also requires that the utility from living in any house is equalized across neighborhoods for each individual in group g. Setting indirect utility (equation 2) to a constant, and taking total differentiation, we show that base rent in a neighborhood increases with an increase in neighborhood safety ($\frac{\partial r_0}{\partial S_j} > 0$) and amenity ($\frac{\partial r_0}{\partial A_j} > 0$). The base rent also increases with an increase in income ($\frac{\partial r_0}{\partial Y_g} > 0$). This means that richer men and women will sort into more expensive neighborhoods.

3.2 Sorting across neighborhoods

The idiosyncratic preference shock ϵ_{igj} ensures that both men and women will live in the same neighborhood, though their proportion in a neighborhood defined in equation (3) will vary depending on their indirect utility. Relative sorting of men and women into neighborhood j is governed by

$$V_{wj} - V_{mj} = (\theta_w - \theta_m)S_j - \alpha \ln\!\left(1 + \frac{\psi}{r_0(S_j, A_j)}\right) + K_1, \tag{7}$$

where $K_1 = [Y_w + \epsilon_{iw} - Y_m - \epsilon_{im}] + \alpha ln[(\alpha\gamma - \theta_w^2)/(\alpha\gamma - \theta_m^2)]$ is neighborhood-invariant term and V_{gj} is the indirect utility function for group g. The first term implies that safer neighborhoods attract relatively more women. The second term implies that where base rents r_0 are higher (e.g., high-amenity locations), the fixed female-specific cost ψ is a smaller fraction of the rent, which also raises female concentration. Women thus sort into high-amenity (A_j) neighborhoods because of ψ, even though they value A_j exactly as men do. Income offers a third explanation, involving neither norms nor safety: the proportion of women in richer neighborhoods can be higher simply because women are richer than men ($K_1 > 0$), for instance if female migrants come from better-off families than male migrants. But income moves women across cities and neighborhoods. It cannot explain rent differences for comparable rooms within the same neighborhood or building.

[12] See appendix for detail derivation.

3.3 Gender gap in Rents

The gender difference in rental can be defined as:

$$r_w^*(S,A) - r_m^*(S,A) = \frac{\alpha\gamma}{(\alpha\gamma - \theta_w^2)}[\psi + \frac{r_0(S_j,A_j)(\theta_w^2 - \theta_m^2)}{(\alpha\gamma - \theta_m^2)}] > 0 \tag{8}$$

The two terms in the bracket correspond to the two sources of the gap. The first is the supply-side cost ψ, which enters one-for-one wherever women rent. The second is the demand side: women's stronger preference for safety is capitalized into rents in proportion to the base rent r_0. Observed rent gaps across neighborhoods therefore mix a sorting channel through $(\theta_w - \theta_m)$, as women sort toward safer and often more expensive neighborhoods and buildings, with a supply channel through ψ, a female-specific markup that is proportionally less binding in high-r_0 neighborhoods. Within a neighborhood, both channels push women into safer and more expensive buildings.

3.4 Within building rental gap

Conditioning on the same building, sorting effects are removed. Any residual female premium is primarily identified as a supply-side wedge, ψ. In a stylized same-unit comparison,

$$\Delta r^{\text{within}} \approx \frac{\alpha\gamma\,\psi}{\alpha\gamma - \theta_w^2} > 0, \tag{9}$$

so larger ψ raises within-building gender rent gaps.

This formalizes the intuition above: within a building, safety and amenities are shared, so sorting cancels and what remains is the landlords' cost. The model thus decomposes gender rent inequality into sorting-driven differences (θ) across neighborhoods and building types, and within-location markups (ψ) that remain for comparable units. Empirically, a large gap that disappears once location and building fixed effects are added points to sorting. A gap that persists for comparable units within the same building points to ψ. The decomposition is central for policy: improving safety works on the sorting margin, while reducing discriminatory frictions shrinks the supply-side markup.

3.5 Gendered preferences/ attitudes or Social norms?

The model so far posits that both θ and ψ are shaped by social norms regarding women's respectability. However, women may intrinsically value safety more than men even in a norm-neutral setting. Similarly, gender-specific supply-side costs may reflect idiosyncratic animus rather than reputational risk and animus induced by social norms. To distinguish these mechanisms, we on the fourth intuition and exploit inter-group variations in both landlord and tenant types.

We start with supply side parameter (ψ). To distinguish between general animus towards women from reputational risk, we decompose ψ into two parts:

$$\psi_\ell = \bar{\psi} + \xi_\ell. \tag{10}$$

Where $\bar{\psi}$ is the component of gender-specific cost that is common across landlord types (for example, broad animus), while ξ_ℓ is reputational risk arising from differential exposure to local gender norms for landlord type [$\ell \in \{l_1, l_2\}$]. For instance, landlords with fewer listings ($l = l_1$) are more rooted in the neighborhood and social ostracism could impose higher burden on them. Using equation (9), the difference in within-building gender premia across landlord types is:

$$\Delta r^S_{l_1}(j) - \Delta r^S_{l_2}(j) = \frac{\alpha\gamma(\xi_{l_1} - \xi_{l_2})}{\alpha\gamma - \theta^2_w}. \tag{11}$$

Thus, the model predicts larger gender gaps among smaller operators if social-norm-based reputational risk is relevant ($\xi_{l_1} > \xi_{l_2}$). By contrast, if gaps are driven only by common animus, differences across landlord types should be insignificant.

Note that $\bar{\psi}$ may still contain two elements: common norm-based behavior shared by all landlords and idiosyncratic animus unrelated to norms. The between-type contrast above wipes out the common norm based behavior and can understate the full role of norms. To isolate common norm effects, one useful benchmark is landlords who rent to both men and women, as they are less likely to be driven by strict exclusionary animus; estimates for this group can help recover the common norm-related component of the rent gap embedded in ($\bar{\psi}$) .

On the demand side, we use differences across female subgroups to distinguish intrinsic gendered preference from norm-induced preference. For instance, students and working women both rent rooms in PGs but students are often financed by parents, whose stronger safety concerns for daughters may amplify effective demand for safer housing. Let female subgroup $q \in \{s, wk\}$ denote students and working women and their preferences are denoted as:

$$\theta_{wq} = \bar{\theta}_w + \nu_q. \tag{12}$$

Where $\bar{\theta}_w$ is the common gendered preference and ν_q is group specific preference induced by variations in exposure to gender norms. Using equation(5) the within-neighborhood premium differences between the two groups becomes:

$$\Delta r_{sm}(j) - \Delta r_{wkm}(j) = [\alpha\gamma(r_{0j} + \psi)] \left[\frac{\theta^2_s - \theta^2_{wk}}{(\alpha\gamma - \theta^2_s)(\alpha\gamma - \theta^2_{wk})} \right]. \tag{13}$$

If the gender gap is driven by women's common intrinsic preference for safety relative to men, then $\theta^2_s = \theta^2_{wk}$ and we should not expect gender rent gaps to differ between the two groups. If students face stronger norm-mediated safety concerns, then $\nu_s > \nu_{wk}$, implying stronger sorting into safer neighborhoods and a larger gender rent gap for students relative to working women.

4 Data

To quantify the gender differential in rents for shared accommodation across cities in India, we compile listing advertisement data from the largest realty platforms in

India from 2021-2024. We construct supplementary data on social norms using the Ethnographic Atlas following Giuliano and Nunn (2018), to provide direct evidence on the extent to which these gender differentials are correlated with the presence of patriarchal social norms.

4.1 Gendered rental listings for shared accommodation

We compile data from major rental advertisement platforms in India, Sri Lanka and Bangladesh from August 2021 to February 2024. This allows us to assemble a dataset of shared accommodation available for rent, including information on tenant gender preferences, and to assess whether rental charges differ based on gender.

While we gather data for all cities from three major listing platforms in India (we term these platforms M, N and O), our main specification uses data from platform N, which offers the richest set of controls.[13] Over 64,500 PGs were advertised on platform N from August 2021 to February 2024, of which 65% listed an explicit gender preference for the tenant. Our main sample will comprise of 43,173 advertisements across 234 cities, of which 48.8% were advertised only for women and 51.2% for men. Given the concentration of PG accommodations in major education and professional hubs, approximately 75% of our sample is located in Delhi NCR, Bangalore, Kolkata, Mumbai, Pune, Chennai, Hyderabad and Ahmedabad. We collect data over a similar time period from the major listing platforms in Sri Lanka and Bangladesh (platforms B and I respectively), which cover major cities across both countries but provide a more limited set of controls than platforms in India. Table 1 outlines all platforms and providers of PGs from which we have obtained data.

Platform M is the second of our three Indian sources. Our platform M sample comprises 60,964 advertisements between August 2021 and May 2024 across 183 cities, of which 48% were advertised only for women and 52% only for men. While platform M covers a comparable set of cities, it records a substantially narrower set of listing characteristics than platform N.[14] Platform N additionally assigns unique identifiers to both buildings and landlord profiles, letting us hold the building or the owner fixed when comparing male- and female-only listings — a feature platform M lacks and that is central to isolating the landlord's gender-specific cost from neighborhood- and building-level sorting. Consequently, we use platform N for our main specification and treat platform M as a cross-platform robustness check.

Landlords or their agents post advertisements on rental platforms, providing detailed information about the location and amenities of the shared accommodations.[15]

[13] Details on data from the other platforms are in Appendix B. We show that results from platform O are consistent with our main results in Appendix C.

[14] For each advertisement we observe the number of tenants sharing a room, whether the listing is verified, and a set of amenities common to both platforms—television, wi-fi, air conditioning, food service, power backup, geyser, microwave, parking, attached bathroom, refrigerator, washing machine, and balcony. Platform M does not, however, report the floor area of the accommodation, its furnishing status, the number of photographs, the age of the listing, or the property's facing, floor level, or corner-unit status—all of which are available on platform N.

[15] 61% of the advertisements on Platform N are directly uploaded by landlords, with the remainder listed by dealers or agents.

Table 1: Summary of observations across all listing data sources

	Country	Obs.	Period	Cities	Uncond. Gender Gap (%)
Platforms					
M	India	60,964	2021-08 - 2024-05	183	5.7***
N	India	43,173	2021-08 - 2024-02	234	4.6***
O	India	63,785	2018-01 - 2020-03	10	2.2***
K	India	53,200	2024-05	9	7.3***
W	India	1,355	2024-05	14	6.0***
B	Bangladesh	4,381	2021-08 - 2024-12	14	6.3***
I	Sri Lanka	12,287	2021-08 - 2024-12	21	8.0***
Providers					
H	India	82	2023-12	2	6.8
S	India	549	2023-12	16	13.2***
Z	India	417	2024-05	9	-8.3

Each advertisement includes basic details such price per individual bed, the number of tenants per room, geographic coordinates and sometimes a name for the building or housing society.[16] Additionally, advertisements often describe various features of the building and room, such as air conditioning, wi-fi, the presence of a balcony, or an attached bathroom. They also detail amenities available in the accommodation, which can be categorized broadly into appliances, meals included or available for pay, laundry services, and access to outdoor spaces or a gym. Table **??** summarizes some of these amenities provided in each shared accommodation.[17]

Table B.1 indicates that although individual amenities in accommodations for women may differ — such as a slightly higher provision of hot water, microwaves, and refrigerators — these are offset by other factors, such as living in older buildings or being less likely to have some other amenities. Table B.1 reveals that, on average, accommodations listed for women do not advertise additional security features or personnel. This may reflect the fact that women sort into safer neighborhoods and do not require as many safety features as men who sort into unsafer places.

To distinguish between rents paid in shared accommodations run as small mom and pop operations and those run by large organizations, we obtain rental listings from the web presence of large, vertically-integrated PG providers. In data from platform N, each poster is assigned a unique ID allowing us to track the provision of PGs by one landlord. Approximately 41% of the PGs in our sample are advertised by landlords with one or two PGs.

[16] Housing societies are a common urban residential arrangement in India, and consist of a cooperatively managed residential complex

[17] Table **??** in Appendix B1 summarizes all variables reported in each advertisement for platform N.

4.2 Social and cultural norms

Gender differentials in rents may be influenced by prevailing social and cultural norms. We measure social norms across cities in India following Giuliano and Nunn (2018), who matched ethnographic data on the social norms and behaviors of ancestral populations (codified in the *Ethnographic Atlas*; Murdock *et al.*, 1999) to a modern map of language distributions from *Ethnologue*.

The primary source of ethnographic information used in our analysis is from the *Ethnographic Atlas*, which provides data on gendered social norms that may influence attitudes towards women and the costs associated with providing housing for them. The Atlas includes information on the pre-industrial characteristics of 1,265 ethnic groups, with 313 of these groups located in various parts of India. It covers a range of social norms across different categories, such as task specialization, inheritance, succession, and settlement patterns. For our study, we focus specifically on those norms that pertain to gender attitudes within these ethnic groups.

We construct four broad social norm measures using the Ethnographic Atlas: prohibition of pre-marital sex, the share of men in various tasks, marriage payments (bride price versus dowry) and patrilineal descent.[18]Anecdotal evidence suggests that a significant "cost" associated with providing housing to single women in India is the perceived risk of behavior deemed inappropriate by societal standards, which could potentially harm the landlord's reputation. To address this, we categorize groups as strictly prohibiting pre-marital sex if they enforce early marriage for females, insist on virginity at marriage, or prohibit pre-marital sexual relations. The second and third measures capture women's societal position through kinship and marriage institutions: whether descent is traced patrilineally or matrilineally, and whether marriage involves bride price paid to the bride's family or dowry paid to the groom's. The fourth measure proxies for norms restricting women's participation in the labor force, based on the historical male share of eight traditional subsistence tasks — metalworking, weaving, leatherworking, pottery, construction, hunting, gathering, and agriculture. A task counts as male-performed if men are solely or predominantly responsible for it; a higher male share reflects a more restrictive gendered division of labor. We then link each rental advertisement to the ancestral social norms of the prevalent ethnic group at each location.

We supplement the ancestral measures with contemporary indicators of gender norms. From the 2019–21 round of the National Family Health Survey (NFHS-5, the Indian implementation of the Demographic and Health Surveys), we measure son preference, female employment, and women's freedom of physical mobility at the district level. At the state level, we construct two indicators: states that reformed gendered inheritance laws ahead of the national Hindu Succession (Amendment) Act of 2005 (Kerala, Andhra Pradesh, Tamil Nadu, Karnataka, and Maharashtra), and matrilineal states as classified by Jayachandran and Pande (2017). We link each advertisement to these measures through the district and state of the listing.

[18]Appendix B6 provides more details on the construction of each norm.

4.3 Safety Data

Our measure of perceived neighborhood level safety comes from SafetiPin, a mobile application — launched in Delhi in November 2013 and now used in 28 cities across 10 countries — through which users conduct "safety audits" of a location. We observe composite scores for over 33,000 audits conducted between May 2017 and March 2020 in Delhi, Hyderabad, Bengaluru, and Kolkata. Each audit rates nine parameters, from lighting, openness, and visibility ("eyes on the street") to the presence of people, the gender composition of that crowd, security personnel, walking paths, access to public transport, and the auditor's overall feeling of safety, each on a scale from 0 (low safety) to 3 (high safety). Appendix Table B5 reports the rubric. Audits are partly crowdsourced and partly conducted by trained auditors, which gives us coverage of the parts of a city that crowdsourced audits alone would miss (Viswanath and Basu, 2015).

4.4 Household survey data

We utilize data from the Household Consumption Expenditure Survey (HCES) conducted by the National Sample Survey Office (NSSO) of the Government of India from August 2023 to July 2024 to estimate the gender gap from actual rental expenditure data. The survey collects information on the consumption of and expenditure on goods and services, including on rent, by households. The HCES surveyed over 400,000 urban households following a multi-stage stratified sampling design with urban blocks or sub-blocks as the First Stage Units (FSU). Of these, 5,432 (1.3%) are never-married men or women between ages 16-65 renting a dwelling alone and comprise our main sample.

5 Empirical Results

We document the gender rent gap in three steps. We begin by presenting the empirical specification we use throughout. We then show how women sort across neighborhoods, establishing the demand-side sorting patterns predicted by the model. Finally, we quantify the gender rent premium and decompose it into demand-side and supply-side components.

5.1 Empirical Specification

We estimate the gender gap in rents by comparing listed prices of male-only and female-only shared accommodations, controlling for a comprehensive set of housing arrangements, amenities, and detailed neighborhood fixed effects. Our primary specification uses data from platform N, which covers PG accommodations in more than 230 cities in India. Formally, we estimate:

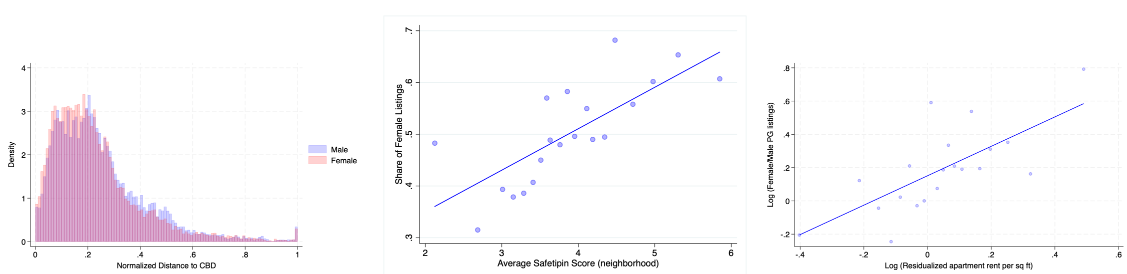
$$Y_{ijt} = \beta_1 G_i + \beta_2 \mathbf{X}_i + \gamma_t + \delta_j + \varepsilon_{ijt} \tag{14}$$

where each observation i is an advertisement for a PG in city (or neighborhood) j posted in month-year t. The sample consists of PGs that explicitly state a preference for tenant gender (we set G_i=1 for female PGs), so β_1 — our coefficient of interest — captures the gender differential in rents between female-only and male-only listings. $\mathbf{X}_i$ is a set of controls for characteristics of the accommodation: number of beds per room, in-room or shared bathroom, age of the building, floor number, furnishing status, and indicators for the cardinal direction an apartment faces. We also control for amenities present within the apartment (like appliances, kitchen, laundry, food service), security provision, and building-level amenities (like gymnasiums and swimming pools). Geographic fixed effects δ_j enter at the city or neighborhood level across different specifications. We include time fixed effects γ_t at the month-year level to control for nationwide seasonality and rent inflation at the time each PG was listed on the platform.[19]

5.2 Sorting across Neighborhoods

Women concentrate closer to the central business district, sort into safer neighborhoods, and are more heavily represented in higher-quality, higher-priced areas, consuming less housing space in per capita square footage terms. These patterns are consistent with the model's prediction that the reputational cost of unsafe living falls disproportionately on women under prevailing social norms.

Figure 2a plots the density of female and male PG listings by normalized distance to the CBD. Women sort closer to the center, where employment is likely to be concentrated. Figure 2b shows that this sorting has a safety dimension: female listings are more prevalent in neighborhoods with higher Safetipin scores. Figure 2c plots the log ratio of female-to-male PG listings against neighborhood quality estimated from apartment listing data. As predicted by the model, the ratio rises with neighborhood quality. Figure 2c also shows that the supply of female PGs is lower than that of male PGs everywhere, but the gap narrows substantially in higher quality and consequently high-priced areas. The model predicts exactly this pattern even when women value amenities no more than men do: the fixed female-specific supply cost ψ is proportionally smaller where base rents are high, so the relative supply of female PGs rises with neighborhood quality.



(a) Distance to the CBD (b) Neighborhood Safety (c) Neighborhood Quality

Figure 2: Gendered Sorting Across Neighborhoods

[19] Our sample from Platform N contains listings from 234 cities and 2523 neighborhoods, which we construct by reverse-geocoding on a popular maps API.

Table 2 quantifies these sorting patterns. We estimate equation 14 with dependent variables describing different aspects of sorting — neighborhood safety scores, a listing-level amenity index, and measures of housing space — including time and location fixed effects but excluding the controls $\mathbf{X}_i$. Odd-numbered columns include city fixed effects; even-numbered columns add neighborhood fixed effects.

Table 2: Sorting of women by safety, amenity and housing unit size

Platform N	Avg Safety Score		Amenity Score		People per room		Area per person	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Advertised for only-females	0.052***	0.039***	0.111***	0.102***	0.012	0.034***	-17.871**	-16.518**
	(0.015)	(0.012)	(0.017)	(0.018)	(0.009)	(0.011)	(7.026)	(7.597)
N	10047	10047	43080	41632	43072	41632	43072	41632
R2	0.336	0.629	0.103	0.225	0.231	0.241	0.149	0.204
Platform M	Avg Safety Score		Amenity Score		People per room			
	(1)	(2)	(3)	(4)	(5)	(6)		
Advertised for only-females	0.098***	0.039***	0.111***	0.122***	0.013*	0.001		
	(0.011)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)		
N	21244	21244	60903	60080	58160	57328		
R2	0.311	0.616	0.188	0.334	0.054	0.102		
Time FE	X	X	X	X	X	X	X	X
City FE		X	X	X	X	X	X	X
Neighborhood FE				X		X		X

Notes: The dependent variable is average safety score in column 1, amenity score in columns 2 and 3, people per room in columns 4 and 5, and area per person in columns 6 and 7 which is only available for platform N. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

We start with safety scores, which are available for four metropolitan cities. Since the scores vary at the neighborhood level, we estimate this regression with city fixed effects only. The evidence confirms that neighborhoods with more female-only listings have higher safety scores. We next construct an amenity index, using characteristics of the rental listed in the advertisement, that counts the number of amenities with positive valuations in the hedonic rent regressions. Female-only listings score higher on this index as well.[20] Finally, we compare housing space. Within neighborhood, female listings have significantly more people per room and female-only properties are also smaller in per capita square footage terms. Women thus sort into safer, higher-amenity locations while consuming less space.

The overall sorting patterns in our listing data are consistent with predictions of the model, and we expect women to pay higher rents than men. In the next subsections, we delve deeper into quantifying the gender gap in rents and examining whether sorting based on pure gender specific preference – not induced by social norms – can explain away this gap.

5.3 Gender gaps in rents

Female-only PG accommodations charge 6–8% more in monthly rent than comparable male-only listings. This gap survives an extensive set of controls, cannot be explained by

[20]The results are robust to alternative definitions of the amenity index.

selection on unobservables, and replicates in household survey data and across South Asian countries.

Following the sequential approach of the conceptual framework in Section 3, Table 3 presents estimates of β_1 from equation (14), our coefficient of interest, with fixed effects and controls added progressively across columns 1 to 6. The upper panel reports results using data from platform N; the lower panel from platform M. Platform N provides the most comprehensive data on observable characteristics of the PGs, so our preferred estimates are in the upper panel.

The estimates of β_1 are positive, economically meaningful, and statistically significant in every specification. The pattern across columns of Table 3 reveals the mechanics of sorting: women sort toward cheaper cities but, within cities, into more expensive neighborhoods. Without location controls (column 1), the estimate is close to the unconditional gap. Adding city fixed effects (column 2) raises the estimated gap: within any given city, the female premium is larger than the national average, because women sort toward cheaper cities. This suggests that women migrating from rural areas do not systematically choose more expensive destinations, as would be expected if they came from more advantaged socioeconomic backgrounds than men. Women do, however, sort into more expensive neighborhoods within a city, so adding neighborhood fixed effects (column 3) brings the coefficient back down.

Observable quality differences explain little of the remaining gap. Columns 4 to 6 add controls progressively: basic features such as room size and furnishing (column 4), internal amenities (column 5), and external characteristics including age, orientation, and floor number (column 6). Each additional control set changes $\hat{\beta}_1$ but the estimate in column 6 is still 81% of the city level gap in column 2. With 81 attributes plus neighborhood and time fixed effects, female-only PGs charge approximately 6–8% more than male-only PGs.

Could unobserved attributes explain away the estimate in column 6? To assess this possibility, we use the methodology proposed by Oster (2019) and estimate the degree of selection on unobservables (δ) needed to drive the $\hat{\beta}_1$ estimate to zero. Setting R_{max} equal to 1.3 times the actual R^2_{within} as Oster (2019) recommends, selection on unobservables would have to be 14 times the degree of selection on observables in platform N data and 11 times in platform M data.[21] We also raised the R_{max} to twice the observed R^2_{within}. The resulting $\hat{\delta}$ estimates are still large ranging between 3.4 in platoform M and 4.4 in platform N. Such large values of $\hat{\delta}$ are implausible given that $\hat{\delta}$'s value in the range $(1 - 1.5)$ is considered as conservative by Oster (2019). Using the same methodology, we also estimate what $\hat{\beta}_1$ would be under the standard assumption that selection on unobservables is equal to that on observables ($\delta = 1$). The lower bound estimates for the gender gap from setting $R_{max} = 2 * R^2_{within}$ are 6.6% in platform N and 4.7% in platform M data.[22] From both of these pieces of evidence, we conclude that the gaps

[21]The implementation of the Oster procedure required some adjustments in the way the regressions are run, as it does not accommodate the reghdfe command in Stata. We use the Stata xtreg command, setting neighborhoods as the source of the main fixed effects; other fixed effects are introduced directly in the regression. For R^2, we focused on within R^2 which are 0.24 for platform N and 0.32 for platform M. R_{max} is set to 1.3 times the within R^2.

[22]For platform N, the overall $R^2 = .606$ and $R^2_{within} = 0.236$ (column 6, Table 3). Doubling R^2_{within} would

in column 6 are unlikely to be driven by unobserved attributes. By contrast, in Harten (2021) the gender gap in rents disappears once controls similar to those in column 5 are included; the gap we document survives the full set of controls.

Table 3: Main specification: Gender differential in rents

	Log (Listing Price)					
Platform N	(1)	(2)	(3)	(4)	(5)	(6)
Advertised for only-females	0.044***	0.099***	0.088***	0.093***	0.088***	0.080***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
N	43173	43080	41632	41624	41624	41555
Avg Listing Price (Male-only, INR)	7551	7555	7596	7597	7597	7595
R2	0.020	0.312	0.500	0.546	0.586	0.606
Platform M						
Advertised for only-females	0.063***	0.087***	0.080***	0.080***	0.062***	0.064***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
N	60947	60903	60080	57328	57328	57328
Avg Listing Price (Male-only, INR)	8043	8045	8063	8169	8169	8169
R2	0.099	0.260	0.455	0.564	0.602	0.609
Time FE	X	X	X	X	X	X
City FE		X	X	X	X	X
Neighborhood FE			X	X	X	X
Basic Features				X	X	X
Controls					X	X
Extended Controls						X

Notes: The table reports results from OLS regressions. The dependent variable in columns 1 through 6 is logarithm of the rent price. All regressions include time fixed effects. Basic features control includes number of tenants sharing a room, area of the apartment in square feet and an indicator for whether the accommodations are furnished for platform N. For platform M, they include the number of tenants sharing a room and area of the apartment. Controls include the common amenities between platform N and platform M: TV, WiFi, AC, microwave, fridge, washing machine, geyser, power backup, bathroom attached, balcony, parking and food service. Extended controls for platform N are the presence of stove, light, bed, fan, wardrobe, curtains, study table, dinning table, modular kitchen, chimney, sofa, swimming pool, club house, vastu compliance, park, garden terrace, security, and gym. It also includes attributes such as: ad verified, photo count, age, facing, floor number and whether it is a corner property. The extended controls for platform M include housekeeping and the number of extra amenities in the ad. The sample for platform N includes 233 different cities. Neighborhood fixed effects were defined using neighborhood tags and the sample includes 2,523 different neighborhoods. The sample for platform M includes 183 different cities, and neighborhood fixed effects include 3,026 different neighborhoods. Robust standard errors in parentheses. Overall sample sizes in this table are smaller than the sample sizes in Appendix Table B.1 because fixed effects regressions drop singleton observations. *** p<0.01, ** p<0.05, * p<0.1.

We check the robustness of our findings in two ways. First, we ask whether similar gaps appear in other South Asian countries with roughly similar gender norms: Tables C.5 and C.6 show that positive and significant gaps exist in Bangladesh (7%) and Sri Lanka (10%) respectively. Second, we ask whether actual rental expenditure data shows the same pattern for India. Using HCES data, we compare rents paid by never-married men and women aged 16–65. Table 4 shows that single women pay 3–4% more than men for rental accommodation, even after controlling for urban block fixed effects and socioeconomic and demographic characteristics. Rent payments are also 1.2 percentage point higher share of household expenditure for women than for men. Note also that the household survey data captures a segment of the market where average rents are

push overall $R^2 = 0.84$

much smaller than those reported in platform advertisements. The household survey data does not typically include the PGs in sample frame. It does not allow us to locate the rentals geographically or provide any characteristics of the housing that is being rented. For the rest of the analysis, we therefore focus on the listing data.

As noted in the data section, the PG market includes a third "unisex" segment in which listings are offered to both men and women at the same posted price. These rentals are often short-term targeting working professionals and are more expensive for landlords to rent out due to search and matching frictions, and higher maintenance and cleaning requirements. In appendix Table C.8, we reproduce the results equivalent to Table 3 while including the unisex segment of the market. Reassuringly, the gender premium remains at 7-7.4% in the specification similar to column 6 in Table 3. Moreover, the premium for unisex segment over male only listings is between 5-15%. At the city level, unisex rentals are substantially more expensive in absolute term: 15-21% more than the average rent paid by men and 6-12% more than that paid by women (column 2, Table C.8). Thus, unisex segment does not provide an affordable option to most women. For them, it would mean paying even more than they currently do in the gendered market.

Table 4: Gender differential in rents from household survey

	Log Rent		Rent as Share of Expenditure
Never-married women (aged 16-65)	0.043**	0.034**	0.012*
	(0.021)	(0.017)	(0.007)
N	4616	4555	4555
Avg Rent (Male-only, INR)	3269	3276	3276
Basic Controls		X	X
Extended Controls		X	X
FSU FE	X	X	X

Notes: The table reports results from OLS regressions, where households are weighted by NSSO sample weights. The dependent variable is the logarithm of rent paid in columns 1 and 2, and the ratio of rent to total household expenditure in column 3. All regressions include FSU fixed effects (942 FSUs). Controls include years and level of education, age, age squared, mean monthly consumption and its square. The ratio of rent to household expenditures averages 0.4 for men and 0.39 for women in the sample. Robust standard errors in parentheses. Overall sample sizes in this table are smaller than the sample sizes in Appendix Table B.1 because fixed effects regressions drop singleton observations. *** p<0.01, ** p<0.05, * p<0.1.

5.4 What drives the gender gaps in rents?

We now decompose the gender-based rent gap into preference heterogeneity (θ_w vs. θ_m) on the demand side and gender-specific costs (ψ) on the supply side, and then ask whether each component is itself driven by social norms. The model in Section 3 guides each step: gaps that shrink with finer location fixed effects point to sorting, while gaps that persist within the same building point to a supply-side wedge.

The gender gap estimated in Table 3 could reflect several forces beyond a gender-specific cost. Even within the same neighborhood, amenities, safety, and transit access vary across locations, and these attributes may be correlated with where female-only PGs locate; this necessitates comparing male-only and female-only PGs within the same building. There may be selection in the types of landlords who operate male-only versus female-only PGs. The size and scale of an operation can affect the costs of supplying accommodation to each gender. And different PGs cater to distinct clienteles, whose demand for female accommodation may differ. We address each of these in turn.

We begin by comparing male-only and female-only PGs within the same building. Column 1 of Table 5 introduces building fixed effects, restricting the sample to PGs with building identifiers and to buildings where we observe at least one male and one female PG. Female-only PGs ask for 5.5% more rent within the same building, which is 69% of the effect size in the comparable full-sample specification (column 6 of Table 3).[23] Comparing this estimate with the raw within-city estimate (0.099 in column 2 of Table 3), we attribute 44% of the within-city gender gap to sorting (θ_w vs. θ_m) and 56% to gender-specific costs (ψ).

A remaining concern is that unobservables *within* the building could drive the within-building gender gap, in which case our estimate of the gender-specific cost parameter (ψ) would be an upper bound. We address this using the Oster (2019) bounding procedure discussed earlier. The within-building regression explains 84% of the variation in log rent, with building fixed effects accounting for the bulk of this explanatory power. We also include 76 observable apartment attributes—floor level, unit orientation, and corner status, among others detailed amenities. Together those controls explain 18% of within-building variation ($R^2_{within} = 0.18$). Setting $R^{max} = 1.3 * R^2_{within}$, our estimates show that the degree of selection on unobservables would have to be 26 times that on observables to drive $\hat{\psi}$ to zero. Even under more conservative restriction of $R^{max} = 2 * R^2_{within}$, the estimated $\hat{\delta}$ is about 8. Under the assumptions that $R^{max} = 2 * R^2_{within}$ and $\delta = 1$, we estimate the lower bound of $\hat{\beta}_1$. The lower bound estimate implies a substantial gender gap of 5% which accounts for 51% of the city-level gap (0.099).

[23]We presume that building unobservables also control for most location unobservables, although large housing societies in India may have multiple entrance gates, with somewhat different street approaches.

Table 5: Gender differential in rents: within-building, within-owner, and by operator size

	Log (Listing Price)					
	Within-Building	Small Operator ($\leq$5 ads)	Large Operator ($>$100 ads)	Within-Owner	Small Operator ($\leq$5 ads)	Large Operator ($>$100 ads)
Advertised for only-females	0.055***	0.127***	-0.001	0.066***	0.029	-0.008
	(0.012)	(0.026)	(0.014)	(0.006)	(0.047)	(0.013)
N	8751	2870	3011	29319	1390	2908
Avg Listing Price (Male-only, in INR)	9483.824	7595.483	10446.974	7876.733	7396.624	10517.881
Time FE	X	X	X	X	X	X
Basic Features	X	X	X	X	X	X
Controls	X	X	X	X	X	X
Extended Controls	X	X	X	X	X	X
Building FE	X	X	X		X	X
Owner FE				X	X	X
City FE				X	X	X
Neighborhood FE				X	X	X

Notes: The table shows the coefficient β_1 from Equation 14. Basic features control includes number of tenants sharing a room,area of the apartment in square feet and an indicator for whether the place is furnished. Controls include TV, WiFi, AC, microwave, fridge, washing machine, geyser, power backup, bathroom attached, balcony, parking, food service, presence of stove, light, bed, fan, wardrobe, curtains, study table, dinning table, modular kitchen, chimney, sofa, swimming pool, club house, vastu compliance, park, garden terrace, security, and gym. It also includes attributes such as: ad verified, photo count, age, facing, floor number and whether it is a corner property. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

To see if gender-specific cost (ψ) is induced by reputational risks or animus towards renting to women, we examine the rental gap by size of operation. Small landlords, who are more closely tied to their local communities, may perceive a higher cost of risky behavior deemed inappropriate by societal standards. If this reputational cost is priced into rents, it could result in smaller landlords charging higher rents to female tenants. In contrast, larger companies running multiple PGs across several cities might not face the same risks: such suppliers should be expected to arbitrage a rent gap that does not correspond to a business cost, and their management may hold more progressive norms than the average supplier. Table 5 confirms this hypothesis: landlords managing fewer than five PGs charge women an average of 13% more than men, while we find no statistically significant gender gap in the segment of larger, more professionalized PG suppliers. This result suggests that ψ is driven by reputational costs arising from conservative social norms.

The between building regression above, however, wipes out the part of gender-specific cost that are induced by social norms but common to all landlords and hence can understate the full role of norms, as shown in the conceptual framework. Landlords who run male-only PGs may differ from those who run female-only PGs in their gender attitudes or operational practices, and this selection could generate a rent gap even without any influence from social norms. However, focusing on landlords who supply both male-only and female-only PGs, women still pay 6.6% more than men for comparable accommodations (Column 4, Table 5). For the next two regressions, we include building fixed effects in addition to owner fixed effects. The sample size for small operators is halved as a result, rendering estimate of β_1 imprecise. Yet, it implies a 2.9% gender premium (8% at the upper bound of 95% confidence interval). This suggests that even within the small operators, the more well off ones with more than one listing (column 5) are better equipped to deal with social sanctions than those with one listing (column 2). The results for large operators remain the same as in column 3 of Table 5. The overall evidence in Table 5 suggests that the observed rent differential is not solely attributable to the pure gendered animus of landlords; it reflects a pervasive trend in rental pricing across genders, consistent with both gender animus and statistical discrimination induced by social norms.

Could gender differences in preferences unrelated to social norms explain the gap? To explore this, we compare renting patterns for different groups of women: students and working women. If the gap is driven by pure gendered preferences and not induced by social norms, it should not vary across these groups, since both are women renting in the same market. Critically, these two groups differ in who makes the housing decision. Students are typically accompanied by parents, who choose and pay for the accommodation. Prevailing norms hold parents responsible for an unmarried daughter's safety and reputation, so their willingness to pay for housing deemed safe and respectable exceeds that of a working woman deciding for herself. Landlords can tap into the heightened anxiety of parents who may also be financially well-off than single working women. Table 6 shows that the gender gap in rents is indeed larger in PGs which prefer students over working women. This suggests that the gender gap in rents cannot be explained by gendered preferences alone, and is rooted more in preferences shaped by conservative social norms.

Table 6: Gender differential in rents by tenant preference

	Log (Listing Price)
	(1)
Advertised for only-females X Students preferred	0.091***
	(0.026)
N	11040
Avg Listing Price (Male-only, in INR)	8078.053
Time FE	X
Basic Features	X
Controls	X
Extended Controls	X
City FE	X
Neighborhood FE	X

Notes: The table shows the coefficient β_1 from Equation 14. All regressions include month-year, neighborhood and city fixed effects. Basic features control includes number of tenants sharing a room,area of the apartment in square feet and an indicator for whether the place is furnished. Controls include TV, WiFi, AC, microwave, fridge, washing machine, geyser, power backup, bathroom attached, balcony, parking, food service, presence of stove, light, bed, fan, wardrobe, curtains, study table, dinning table, modular kitchen, chimney, sofa, swimming pool, club house, vastu compliance, park, garden terrace, security, and gym. It also includes attributes such as: ad verified, photo count, age, facing, floor number and whether it is a corner property. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

To summarize, both preference heterogeneity and the higher cost of supplying rentals to women contribute to the observed gender gap in rents. Evidence also suggests that both are rooted mostly in gendered social norms that hold women to higher standards of respectability. In the next section, we provide supporting evidence on the role of these norms.

6 Role of social norms

Gender norms, both ancestral and contemporary, predict where the gender gap in rents is large. Among ancestral norms, the gap disappears once we account for prohibitions against pre-marital sex, and in regions where men historically performed a larger share of subsistence tasks. Among contemporary norms, the gap is about 30% smaller in states that reformed inheritance laws early, and smaller in districts with higher female employment and freedom of mobility.

We utilize geographical variations in gender norms to provide supporting evidence on their role in driving the gender gap in rents. In areas where prevailing social norms may be misogynistic and disapproving of women living independently away from their parents' home, landlords may require additional compensation to be induced to supply to women. Anecdotal evidence suggests that landlords may be concerned about potential damage to their reputation due to perceived inappropriate behavior associated with housing single women.[24] We measure ancestral norms using the Ethnographic Atlas, following the methodology of Giuliano and Nunn (2018), and classify communities as strictly prohibiting pre-marital sex if they enforce early marriage, mandate virginity at marriage, or prohibit pre-marital sexual relations.

The model in section 3 established that social norms lead women to prefer high-amenity neighborhoods even when their underlying preference for amenities is identical to men's. Regressions in this section therefore include fixed effects at the city level rather than the neighborhood level, so that norm-induced sorting across neighborhoods is not absorbed. We estimate the regressions on the full sample of cities and include the full set of extended controls used throughout the paper.

The empirical specification adds to equation 14 an interaction between each social norm and the gender preference of the PG, G_i. Figure 3a shows the coefficients of the female-only dummy (diamond) and its interaction with social norms (circle), one row per norm. The gender rent gap becomes statistically insignificant once we account for the interaction with strict prohibitions against pre-marital sex: the gap is larger in areas with stricter sexual prohibitions.

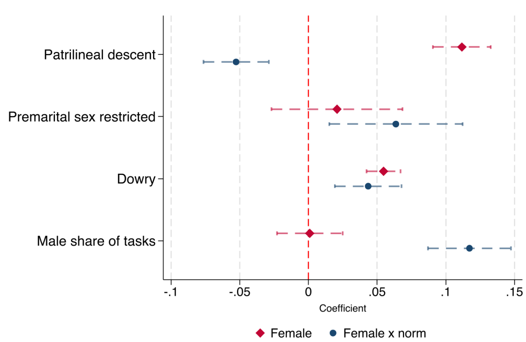
Attitudes towards women's participation in the labor force may also affect rent differentials by gender. To assess these attitudes, we measure the proportion of tasks traditionally performed by men, such as metalworking, weaving, leather-working, pottery, construction, hunting, gathering, and agriculture. A task is considered to be performed by men if they are either solely or predominantly responsible for it. The

[24] The social attitude toward renting to unmarried women was succinctly expressed in a BBC interview by Suruchi Sharma, an educated female manager in digital marketing living in Mumbai: *"...There have been many occasions when I have tried to rent an apartment in a good locality and been refused. People don't like to rent apartments to single, professional women. They are afraid that someone like me will behave immorally - have loud parties, have men to stay overnight, be a bad influence on the surrounding families..."*

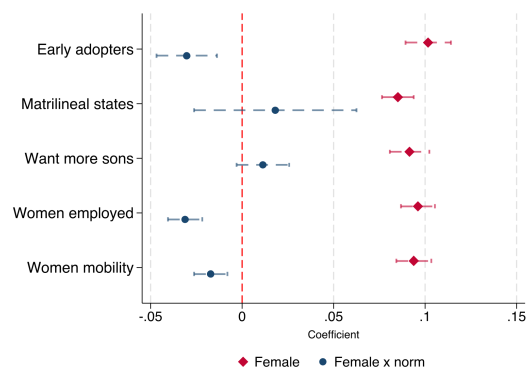
estimates in Figure 3a show that the gender rent gap becomes statistically insignificant in regions where men were responsible for more of these tasks, consistent with broader misogynistic norms raising rents for single women. As a robustness check, we re-estimate these regressions excluding listings in the six largest metropolitan areas: Delhi, Kolkata, Chennai, Mumbai, Bangalore, and Hyderabad (Appendix Table C.11). The interactions with patrilineal descent, dowry, strict prohibitions against pre-marital sex and male task share are similar in magnitude and remain significant.

The gender gap also declines with contemporary indicators of female empowerment. Figure 3b plots coefficients of female-only and its interaction with current norms in a format similar to Figure 3a. The gap is about 30% smaller in states that reformed gendered inheritance laws ahead of national legislation passed in 2005,[25] and is smaller in districts where a larger proportion of women are employed and where women have greater freedom of physical mobility. We find no evidence that the gap is smaller in "matrilineal" states, as classified by Jayachandran and Pande (2017). None of the current norms, however, can fully wipe out the gender gap in rent.

We construct two summary indices of these norms. The ancestral index averages four standardized components, each signed so that larger values indicate more egalitarian norms: premarital sex freely permitted, bride price, matrilineal descent, and the male share of subsistence tasks (reversed). The contemporary index averages five standardized components, signed the same way: son preference (reversed), female employment, freedom of physical mobility, the early-adopter indicator, and the matrilineal indicator. Both indices are standardized after averaging. We plot the gender rent penalty against each index in Figure 4: the penalty declines steadily as norms become more egalitarian, for both ancestral and contemporary measures.



(a) Ancestral norms



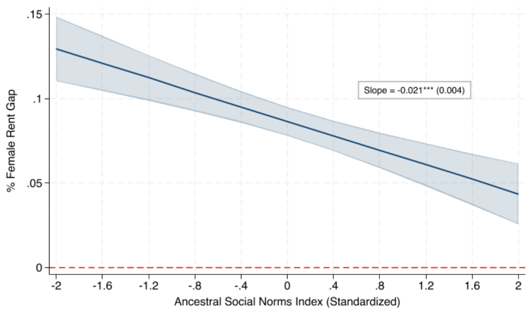
(b) Contemporary norms

Figure 3: Social norms and gender gap in rent

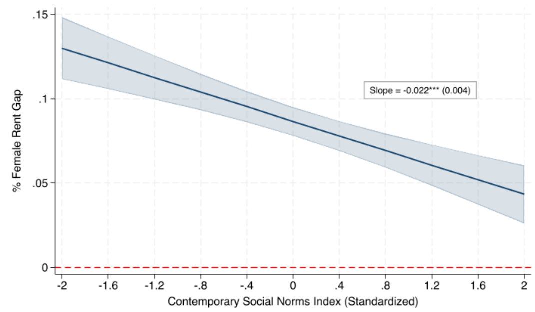
Notes: Each panel shows the coefficient on the female-only indicator (diamond) and its interaction with the listed norm (circle), from the same regression, with 95% confidence intervals. All regressions include extended controls, as well as month-year and city fixed effects.

The evidence in this section shows that gender norms rooted in ancestral customs is

[25] Hindu Succession (Amendment) Act, 2005.



(a) Ancestral social norms



(b) Contemporary social norms

Figure 4: Variation in Gender Rent Gap by Social Norms Index

Notes: Both panels plot the female rent gap against a standardized index of social norms, with 95% confidence intervals; see Appendix B6 for index construction details.

positively associated with a gender penalty in the contemporary housing market. The penalty is smaller where women are empowered through equitable succession laws, greater labor force participation, and freedom of physical mobility.

7 Conclusion

This paper documents a robust gender gap in shared rental housing prices in South Asia and provides evidence on its sources. Using detailed PG listing data from India, we find that accommodations listed for women are priced about 6–8% above comparable listings for men, even after controlling for extensive observed characteristics and granular neighborhood fixed effects. Such a large gap cannot be explained away by any plausible degree of selection on unobservables. We find similar gaps in Sri Lanka and Bangladesh, and in actual rental expenditure data from household surveys in India.

Guided by our conceptual framework, we decompose this gap into demand-side sorting and supply-side frictions. Women sort into safer and higher-amenity locations, but sorting accounts for about half of the within-city premium. A significant gap (51-56%) remains within the same building for comparable rentals, indicating an important female-specific supply-side cost component.

Evidence suggests that social norms both shape women's preferences and generate the additional costs priced by landlords. The within-building premium is largest among small, locally embedded operators and weakens or disappears among larger, professionalized suppliers. This pattern is consistent with female-specific costs tied to reputational concerns and social sanctions in conservative settings. Similarly, compared with working women, the gap is larger for female students whose parents tend to be more sensitive to gender norms.

We provide supporting evidence for this mechanism using spatial variation in social norms. The gender rent gap is strongest in places with stricter norms around women's sexual behavior and in areas with historically higher male participation in productive tasks. Taken together, these results suggest that the housing premium faced by single women is a manifestation of persistent patriarchal norms.

The pink tax raises the cost of taking an urban job and thus affordable rental housing is an important labor market policy for single women. Our decomposition indicates where interventions should aim. Since supply-side costs account for considerable portion of the gap, the priorities are enforcement against discriminatory pricing, incentives to expand safe and affordable housing supply for women, and regulation that lowers the perceived reputational risk of renting to single women. The absence of a gap among large, professionalized operators points to a market-based solution. As urban migration and delayed marriage continue to rise, reducing this housing pink tax can relax a key constraint on women's economic mobility.

Our analysis points to several areas for future research. Online platforms may capture the segment of the PG market that serves relatively well-off residents. Although our sample sizes are large, we do not claim that they are nationally representative. Typical household surveys exclude institutional setting such as PG housing and dormatories from their sample frame. A detailed, nationally representative survey of PG residents would help address both issues. Our findings also suggest that gender animus or gendered preferences play a relatively small role in explaining the gap. Instead, social-norm-induced discrimination on the supply side and gendered preferences on the demand side appear to be the primary drivers. Further research on these mechanisms would help refine the policy implications.

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Appendix A Model

A1 Preferences

We assume that the city is closed and the total number of workers is $L = L_w + L_m$.[26] Each worker uses one unit of housing but housing space can vary. To focus on the mechanisms through which social norms regarding respectability affect different aspects of housing demand and supply, we abstract from commuting concerns. The city has neighborhoods $j \in \{1, \ldots, J\}$, characterized by an exogenous safety level S_j and a secondary exogenous amenity A_j (e.g., parks, transit access). Individuals belong to gender groups $g \in \{w, m\}$ (women and men), where women have a higher preference for safety ($\theta_w > \theta_m$), but both genders equally value the general amenity A_j with preference parameter β. The difference in preference parameters for safety ($\theta_w > \theta_m$) reflects the fact that social norms dictates women to maintain higher standard of respectability than men. It is possible that women may prefer safety more than men even in the absence of social norms. The difference in safety parameters will capture this difference in intrinsic gendered preference as well. [27]

An individual i of group g choosing neighborhood j and house type k maximizes utility:

$$U_{igjk} = C_g + \alpha \ln H_{jk} + \theta_g(S_j + T_{jk}) + \beta A_j + \epsilon_{igjk} \tag{15}$$

The budget constraint is defined as:

$$Y_g = C_g + r_{jk} H_{jk} \tag{16}$$

where C_g is consumption, T_{jk} is landlord-provided safety abatement (locks, cameras, gated access). r_{jk} is rent/space/sq feet for house type k in neighborhood j and H_{jk} is the housing space (square footage). ϵ_{igj} is an idiosyncratic preference shock following a Type I Extreme Value (Gumbel) distribution.

From the first-order condition ($H_{jk} = \alpha / r_{jk}$), the indirect utility V_{gjk} can be derived as:

$$V_{gjk} = Y_g - \alpha + \alpha \ln \alpha - \alpha \ln r_{jk} + \theta_g(S_j + T_{jk}) + \beta A_j + \epsilon_{igj} \tag{17}$$

Given the distribution of ϵ, the share of individuals of group g that chooses house type k in neighborhood j is given by the Logit formula:

$$P_{gjk} = \frac{\exp(V_{gjk})}{\sum_{j'=1}^{J} \sum_{k'=1}^{K} \exp(V_{gj'k'})} \tag{18}$$

[26]We can assume an open city where workers can also choose their destination city. This would mean that utility will be equalized to a reservation utility level determined outside the city, e.g., in a rural location.

[27]In empirical analysis, we conduct heterogeneity analysis by women's characteristics (e.g., student vs. working) to gauge relative importance of this difference in purely gendered preference.

A2 Housing Supply

In each neighborhood j, landlords offer a menu of house types k. We introduce a compensating differential to represent a "reputation cost" or friction landlords face when supplying housing to females. This could arise because landlords may fear incurring a "reputation cost" that renting out to women may lead to future losses if women behave in ways that are socially unacceptable. Social norms can also induce animus in terms a psychological cost to renting to women by landlords. Let ψ_g be this per-square-foot cost markup, where $\psi_w = \psi > 0$ and $\psi_m = 0$.

The landlord's profit function is:

$$\pi = (r(S_j, A_j, T_{jk}) - \psi_g)H_{jk} - P_j H_{jk} - C(T_{jk}) \tag{19}$$

where P_j is the price of floor space in square meter, and $C(T_{jk}) = \gamma T_{jk}^2/2$ is the cost of abetment. The landlord sets the marginal cost of abetment equal to the marginal willingness to pay of the target resident group. For the house type targeted at group g:

$$H_{jk}\frac{\partial r_g}{\partial T_{jk}} = \gamma T_g = \theta_g \implies T_g^* = \theta_g/\gamma \tag{20}$$

Since $\theta_w > \theta_m$, landlords provide higher abetment in units targeted at women ($T_w^* > T_m^*$). Landlords install exactly as much safety as the target group is willing to pay for, so provision is a pricing decision rather than a courtesy.[28] The cost mark-up ψ_g acts as a fixed marginal penalty and does not alter the first-order condition for abetment provision.

A3 Sorting within neighborhood

Integrating the willingness to pay condition for safety (derived by setting $\frac{\partial V_{jk}}{\partial T_{jk}} = 0 => \frac{\partial r_{jk}}{\partial T_{jk}} = \frac{\theta_g}{H}$), and assuming a base competitive neighborhood rent $r_0(S_j, A_j)$, we can recover the rent function incorporating the per-square-foot cost markup ψ_g as:

$$r_g(S, A, T) = r_0(S_j, A_j) + \psi_g + \frac{\theta_g T^*}{H} = r_0(S_j, A_j) + \psi_g + \frac{\theta_g^2}{\gamma H} \tag{21}$$

We can now solve for equilibrium floor space:

$$H_g^* = \frac{\alpha}{r_g(S_j, A_j, T_{jk})} = \frac{\alpha\gamma H_g^*}{\gamma(r_0(S_j, A_j) + \psi_g)H_g^* + \theta_g^2} \tag{22}$$

[28]If we allow abatement cost to depend on neighborhood level safety, then the model will predict optimal safety to vary with average neighborhood safety. If abatement cost increases with neighborhood safety, then landlords will provide less T^* in safer neighborhoods. We abstract from this possibility for simplicity.

$$H_g^* = \frac{\alpha\gamma - \theta_g^2}{\gamma(r_0(S_j, A_j) + \psi_g)} \tag{23}$$

Assuming that $\alpha\gamma > \theta_g^2$ and substituting H_g^* back into the rent function yields the equilibrium rent:

$$r_g^*(S, A, T) = (r_0(S_j, A_j) + \psi_g)\frac{\alpha\gamma}{\alpha\gamma - \theta_g^2} \tag{24}$$

Since $\theta_w > \theta_m$ and $\psi_w > 0$, women consume strictly smaller floor space ($H_w^* < H_m^*$) and pay higher rent ($r_w^* > r_m^*$). The two forces compound: women's higher valuation of safety is capitalized into the rent of the units they choose, and landlords pass the gender-specific cost through to the price per square foot. Facing a higher price, women respond by economizing on space.

A4 Sorting within building

The idiosyncratic preference shock ensures that both men and women live in the same neighborhood. For men with high preference for safety ($\theta_m \approx \theta_w$), they will also live in the same building with similar apartment/room characteristics. The gender difference in rental within a building can thus be approximated as:

$$r_w^*(S, A, T) - r_m^*(S, A, T) = \frac{\alpha\gamma\psi}{\alpha\gamma - \theta_w^2} > 0 \tag{25}$$

Note that if $\psi_w = 0$, then $r_w^* = r_m^*$. Because of extra rent imposed by landlords concerned about reputational risk, women end up paying higher rent for the same housing unit than men even within a building. Moreover, the higher is ψ, the higher is the rental gap between women and men.

This formalizes the third intuition above: within a building, safety and amenities are shared, so sorting cancels and what remains is the landlords' cost. The model thus decomposes gender rent inequality into sorting-driven differences (θ) across neighborhoods and building types, and within-location markups (ψ) that remain for comparable units. Empirically, a large gap that disappears once location and building fixed effects are added points to sorting. A gap that persists for comparable units within the same building points to ψ. The decomposition is central for policy: improving safety works on the sorting margin, while reducing discriminatory frictions shrinks the supply-side markup.

A5 Equilibrium Conditions

Market Clearing: Rents r_{jk} adjust such that total expected demand equals total housing supply N:

$$\sum_{j,k} \left(L_w P_{wjk} + L_m P_{mjk}\right) = N \tag{26}$$

Equilibrium also requires utility level of living in any house is equalized across neighborhoods for each individual in a group g.

$$\overline{u}_{ig} = Z_g - \alpha lnr_0(S_j, A_j) + \theta_g S_j + \beta A_j + \epsilon_{igj} \tag{27}$$

where $Z_g = Y_g - \alpha + \alpha ln[(\alpha\gamma - \theta_g^2)/\gamma]$. It follows from the total differentiation of the above equation that base rent in a neighborhood increases with an increase in neighborhood safety ($\frac{\partial r_0}{\partial S_j} > 0$) and amenity ($\frac{\partial r_0}{\partial A_j} > 0$). The slope of rent function with respect to safety is also steeper for women than men. The base rent also increases with an increase in income ($\frac{\partial r_0}{\partial Y_g} > 0$).

A6 Sorting across neighborhoods and Comparative Statics

To see if women disproportionately sort into safer or high-amenity neighborhoods, we examine the ratio of choice probabilities between women (w) and men (m) for a given neighborhood j. Grouping terms that do not depend on the specific attributes of neighborhood j into a constant $K[= \frac{\sum_{j'=1}^{J}\sum_{k'=1}^{K}\exp(V_{wj'k'})}{\sum_{j'=1}^{J}\sum_{k'=1}^{K}\exp(V_{mj'k'})}]$:

$$\frac{P_{wj}}{P_{mj}} = K \cdot \exp(V_{wj} - V_{mj}) \tag{28}$$

Substituting the deterministic utilities and grouping the rent and safety terms, we isolate the difference in utility derived from neighborhood j. Note that βA_j cancels out directly:

$$V_{wj} - V_{mj} = (\theta_w - \theta_m)S_j - \alpha\ln(r^*_{wjk}) + \alpha\ln(r^*_{mjk}) + [Y_w + \epsilon_{iwj} - Y_m - \epsilon_{imj}] \tag{29}$$

Substituting the equilibrium rents r^*_g and simplifying the logarithmic difference:

$$K_{wm} - \alpha\ln(r_0(S_j, A_j) + \psi) + \alpha\ln(r_0(S_j, A_j)) = K_{wm} - \alpha\ln\left(1 + \frac{\psi}{r_0(S_j, A_j)}\right) \tag{30}$$

where $K_{wm} = \alpha ln[(\alpha\gamma - \theta_w^2)/(\alpha\gamma - \theta_m^2)]$. Thus, the utility difference dictating relative sorting is:

$$V_{wj} - V_{mj} = (\theta_w - \theta_m)S_j - \alpha\ln\left(1 + \frac{\psi}{r_0(S_j, A_j)}\right) + K_1 \tag{31}$$

where $K_1 = [Y_w + \epsilon_{iwj} - Y_m - \epsilon_{imj}] + \alpha ln[(\alpha\gamma - \theta_w^2)/(\alpha\gamma - \theta_m^2)]$ is neighborhood-invariant term and V_{gj} is the indirect utility function for group g. The first term implies that safer neighborhoods attract relatively more women. The second term implies that where base rents r_0 are higher (e.g., high-amenity locations), the fixed female-specific cost ψ is a smaller fraction of the rent, which also raises female concentration. Women thus sort into high-amenity (A_j) neighborhoods because of ψ, even though they value A_j exactly as men do. Income offers a third explanation, involving neither norms nor safety: the proportion of women in richer neighborhoods can be higher simply because women are richer than men ($K_1 > 0$), for instance if female migrants come from better-off families than male migrants. But income moves women across cities and neighborhoods. It cannot explain rent differences for comparable rooms within the same neighborhood or building.

Comparative Static 1: Sorting by Safety (S_j)

Taking the derivative with respect to neighborhood safety S_j:

$$\frac{\partial}{\partial S_j}(V_{wj} - V_{mj}) = (\theta_w - \theta_m) + \frac{\alpha\psi}{r_0(r_0+\psi)}\frac{\partial r_0}{\partial S_j} > 0 \tag{32}$$

Increased safety raises base rents ($\partial r_0/\partial S_j > 0$), it diminishes the relative percentage burden of the fixed cost ψ, making the neighborhood even more attractive to women.

Comparative Static 2: Sorting by Neutral Amenity (A_j)

Taking the derivative with respect to the general amenity A_j:

$$\frac{\partial}{\partial A_j}(V_{wj} - V_{mj}) = \frac{\alpha\psi}{r_0(r_0+\psi)}\frac{\partial r_0}{\partial A_j} > 0 \tag{33}$$

Even though both genders value A_j equally, an increase in A_j strictly increases the relative concentration of women. As A_j rises, the competitive base rent $r_0(S_j, A_j)$ increases, diluting the relative weight of the fixed reputational cost penalty ψ.

A7 Gendered preferences or Social norms?

The model so far posits that both θ and ψ are shaped by social norms regarding women's respectability. However, women may intrinsically value safety more than men even in a norm-neutral setting. Similarly, gender-specific supply-side costs may reflect idiosyncratic animus rather than reputational risk and animus induced by social norms. To distinguish these mechanisms, we rely on the fourth intuition and exploit inter-group variations in both landlord and tenant types.

We start with supply side parameter (ψ). To distinguish between general animus towards women from reputational risk, we decompose ψ into two parts:

$$\psi_\ell = \bar{\psi} + \xi_\ell. \tag{34}$$

Where $\bar{\psi}$ is the component of gender-specific cost that is common across landlord types (for example, broad animus), while ξ_ℓ is reputational risk arising from differential exposure to local gender norms for landlord type [$\ell \in \{l_1, l_2\}$]. For instance, landlords with fewer listings ($l = l_1$) are more rooted in the neighborhood and social ostracism could impose higher burden on them. Using equation (9), the difference in within-building gender premia across landlord types is:

$$\Delta r^S_{l_1}(j) - \Delta r^S_{l_2}(j) = \frac{\alpha\gamma(\xi_{l_1} - \xi_{l_2})}{\alpha\gamma - \theta_w^2}. \tag{35}$$

Thus, the model predicts larger gender gaps among smaller operators if social-norm-based reputational risk is relevant ($\xi_{l_1} > \xi_{l_2}$). By contrast, if gaps are driven only by common animus, differences across landlord types should be insignificant.

Note that $\bar{\psi}$ may still contain two elements: common norm-based behavior shared by all landlords and idiosyncratic animus unrelated to norms. The between-type contrast above wipes out the common norm based behavior and can understate the full role of norms. To isolate common norm effects, one useful benchmark is landlords who rent to both men and women, as they are less likely to be driven by strict exclusionary animus; estimates for this group can help recover the common norm-related component of the rent gap embedded in $(\bar{\psi})$.

On the demand side, we use differences across female subgroups to distinguish intrinsic gendered preference from norm-induced preference. For instance, students and working women both rent rooms in PGs but students are often financed by parents, whose stronger safety concerns for daughters may amplify effective demand for safer housing. Let female subgroup $q \in \{s, wk\}$ denote students and working women and their preferences are denoted as:

$$\theta_{wq} = \bar{\theta}_w + \nu_q. \tag{36}$$

Where $\bar{\theta}_w$ is the common gendered preference and ν_q is group specific preference induced by variations in exposure to gender norms. Using equation(5) the within-neighborhood premium differences between the two groups becomes:

$$\Delta r_{sm}(j) - \Delta r_{wkm}(j) = [\alpha\gamma(r_{0j} + \psi)] \left[\frac{\theta_s^2 - \theta_{wk}^2}{(\alpha\gamma - \theta_s^2)(\alpha\gamma - \theta_{wk}^2)} \right]. \tag{37}$$

If the gender gap is driven by women's common intrinsic preference for safety relative to men, then $\theta_s^2 = \theta_{wk}^2$ and we should not expect gender rent gaps to differ between the two groups. If students face stronger norm-mediated safety concerns, then $\nu_s > \nu_{wk}$, implying stronger sorting into safer neighborhoods and a larger gender rent gap for students relative to working women.

Appendix B Data

B1 Listings platforms in India

This paper uses data on advertised residential rental listings collected from the largest realty platforms in India from 2021-2024, which we will call M, N and O.

Platform M covers August 2021 to May 2024: 183 cities in 29 states and union territories, with both owner- and broker-posted advertisements. The unit of observation is an advertisement i for property p. We deduplicate in two steps. First, we drop listings downloaded on multiple dates that are identical in all fields except download date and file page, keeping the latest download. Second, observations sharing an ad ID but located more than 1.5 km apart are treated as distinct listings unless their locality and city fields match, and one of them receives a synthetic extended identifier (ad ID + 1,000,000). We fill missing tenant gender preferences from keywords in the free-text description and the PG name. We validate coordinates against an India bounding box: for points outside it, we swap latitude and longitude, retain the observation if the swapped pair falls inside the box, and drop it otherwise. We construct one indicator per reported amenity (TV, Wi-Fi, food service, washroom, AC, room cleaning, power backup, fridge, geyser, washing machine, microwave, balcony, and parking) and a count of any additional listed features.

Platform N covers August 2021 to February 2024: 234 cities in 26 states and union territories, with both owner- and broker-posted advertisements. We drop listings that are identical in all fields except download date, file name, and number of completed amenities, keeping the latest download with the most complete amenity information. We construct an extended profile identifier by filling missing profile IDs from earlier advertisements with the same ad ID and, failing that, from the profile start date field. We construct an extended building identifier within each profile-building name pair: where the original building ID is missing and the first and last recorded coordinates are more than 1 km apart, we assign the encoded building name; otherwise we retain the original building ID. The final unit of observation is the combination of ad ID, property ID, extended profile ID, and extended building ID, keeping the latest observation of each. Missing tenant gender preferences are inferred from keywords in the heading, subheading, and description. Prices are winsorized. Tracked amenities include swimming pool, power backup, clubhouse, parking, park, terrace garden, security personnel, central AC and AC, ATM, gym, fire alarm, visitor parking, intercom, lift, maintenance staff, water storage, waste disposal, rainwater harvesting, bank attached, gas pipeline, Wi-Fi, wheelchair accessibility, food service, and laundry room.

Table B.1: Attribute Averages for Female and Male PGs in portal N

	All sample	Female	Male	Diff. (f-m)
Average price winsor	7810.47	8083.97	7550.28	533.69
	(5462.14)	(5904.88)	(4990.94)	(10.12)
Number of people sharing room	2.08	2.07	2.08	-0.02
	(1.05)	(1.01)	(1.08)	(-1.54)
Age of the builiding	2.47	2.55	2.39	0.16
	(1.02)	(1.03)	(1.00)	(16.08)
Corner property: yes/no	0.13	0.14	0.12	0.02
	(0.33)	(0.35)	(0.32)	(6.80)
Area in sqft	1013.93	1019.30	1008.82	10.48
	(1051.37)	(1085.20)	(1018.14)	(1.03)
Floor number	4.09	4.20	3.97	0.23
	(1.59)	(1.61)	(1.57)	(15.02)
Balcony attached	0.37	0.43	0.32	0.10
	(0.48)	(0.49)	(0.47)	(21.82)
Bathroom attached	0.59	0.60	0.57	0.03
	(0.49)	(0.49)	(0.49)	(6.92)
Amenities: natural light	0.11	0.12	0.10	0.01
	(0.31)	(0.32)	(0.30)	(4.93)
Amenities: high ceiling	0.08	0.08	0.08	0.00
	(0.27)	(0.27)	(0.27)	(1.56)
TV (structured+RE). Features	0.44	0.44	0.45	-0.01
	(0.50)	(0.50)	(0.50)	(-2.89)
WiFi (structured+RE)	0.43	0.43	0.44	-0.01
	(0.50)	(0.49)	(0.50)	(-1.37)
AC (structured+RE). Features	0.45	0.48	0.42	0.06
	(0.50)	(0.50)	(0.49)	(11.59)
Amenities: food service	0.15	0.16	0.13	0.03
	(0.35)	(0.37)	(0.34)	(8.88)
Amenities: laundry service	0.14	0.15	0.13	0.02
	(0.35)	(0.35)	(0.34)	(4.60)
Geyser (structured+RE). Features	0.63	0.67	0.59	0.08
	(0.48)	(0.47)	(0.49)	(16.43)
Microwave (structured+RE). Features	0.20	0.23	0.17	0.06
	(0.40)	(0.42)	(0.38)	(14.91)
Fridge (structured+RE). Features	0.58	0.64	0.53	0.11
	(0.49)	(0.48)	(0.50)	(22.86)
Wash.M. (structured+RE)	0.37	0.35	0.39	-0.03
	(0.48)	(0.48)	(0.49)	(-7.23)
Amenities: power backup	0.03	0.02	0.04	-0.02
	(0.17)	(0.14)	(0.20)	(-13.10)
Amenities: lift(s)	0.25	0.23	0.26	-0.04

	(0.43)	(0.42)	(0.44)	(-9.40)
Amenities: gymnasium	0.10	0.09	0.10	-0.01
	(0.29)	(0.28)	(0.30)	(-5.26)
Amenities: park	0.26	0.28	0.24	0.04
	(0.44)	(0.45)	(0.43)	(9.52)
Amenities: security personnel	0.14	0.12	0.15	-0.03
	(0.35)	(0.33)	(0.36)	(-8.88)
Amenities: security/fire alarm	0.18	0.16	0.21	-0.04
	(0.39)	(0.37)	(0.40)	(-11.40)
Observations	43176	21050	22126	43176

Platform O covers January 2018 to March 2020: 10 cities in 9 states and union territories, with both owner- and broker-posted advertisements. We standardize core fields (dates, prices, titles, descriptions), normalizing case, punctuation, diacritics, spacing, number formats, and common abbreviations and misspellings. Duplicates, detected from composite keys combining title or description, locality, price, and posting date or month, are resolved by keeping the newest observation. We screen out records outside our scope (sales or leases of whole buildings or businesses, product or service advertisements, and party, resort, or hourly listings) using keyword rules, and trim implausible prices and a small set of hand-flagged outliers. Female and male indicators are constructed from keywords in titles and descriptions, with explicit handling of negations (“not for men/women”); conflicts between the two are resolved by prioritizing signals in the title. The most relevant amenities on this platform are WiFi, AC, parking, housekeeping, and washing machine.

B2 Spatial identifiers for cities and neighborhoods

This section describes the spatial identifiers that we construct for property listings in platforms M and N.

B2.1 City identifiers

Listings platforms report property coordinates at varying levels of spatial precision, with some properties identified at the level of a building or street address, and some identified at centroids of a proprietary, platform-specific neighborhood or town classification. In addition, every property contains free-text city and "locality" fields, which in some cases are inconsistent with listing coordinates. We adjudicate city identifiers by reconciling (i) the platform’s cleaned text claim, mapped through a crosswalk to canonical metro codes (using labels from the GHS Functional Urban Area codes, see European Commission. Joint Research Centre., 2019) and the listing’s coordinates, spatially joined to buffered geographic layers (FUA polygons, city polygons from Akbar *et al.* (2023), Census-2011 districts, and state boundaries.

In order, we (1) accept listings whose coordinates fall inside the claimed metro’s FUA, or within its 10-20 km buffers; (2) fall back to the locality text when the city field fails but the locality identifies the FUA the point sits in; (3) accept matches against ACDS city polygons and their buffers; (4) validate claims made at the district or state level (e.g., a "city" field naming a district) against the district or state the coordinates fall in; and lastly (5) apply a short hand-curated exception list for naming idiosyncrasies that were found in the data. Listings that no rule can reconcile, and listings that revert to a set of garbage-coordinate clusters, are dropped (about 0.6% of the platform-N file). The resulting metro code is interacted with the state the coordinates fall in, so that metropolitan areas straddling state lines (the National Capital Region, Chandigarh, Bangalore-Hosur) are split into markets by state.

B2.2 Neighborhood identifiers and polygons

Our neighborhood units ("gtags") are built in two steps: coordinates are first labeled with a hierarchy of place names from a commercial reverse-geocoding service, and the labeled point clouds are then converted into mutually exclusive neighborhood polygons by a geometric carving algorithm. An advantage of this construction over administrative units is that it is available at a fine resolution in every city, and that our neighborhoods reflect boundaries used in defining housing markets.

Reverse geocoding and tag hierarchy. We submit the coordinates of every listing to the Google Maps reverse-geocoding API. The tagged universe is deliberately larger than the paying-guest sample: alongside the roughly 75,000 unique PG coordinates from platforms N and M, we tag the far larger sets of coordinates from those platforms' general apartment rental listings (roughly 220,000 additional coordinates), together with some additional points-of-interest for a database of about 340,000 unique tagged coordinates. Densifying the point cloud in this way matters for the geometry in step two: neighborhood shapes are constructed from all rental-market points, not only from the PGs analyzed in this paper.

Each API response reports, for a coordinate, a nested list of political place attributes. We retain, in coarse-to-fine order: administrative area levels 1-4 (state, division, district, sub-district), *locality* (the city or town), and sublocality levels 1-3, with up to three further sub-sublocality components recovered from the street-address result. Raw components are harmonized before use: vernacular-script names are mapped to their English forms, casing is standardized, a component is blanked when it merely repeats its parent (e.g., a "sublocality" identical to the locality), and a small number of instabilities in API responses (e.g., sector naming in Gurugram and Dwarka) are standardized.

A *gtag at resolution r* is the concatenation of the first *r* fields of this hierarchy. We construct nine resolutions, from `gtag_a3` (state-division-district) through `gtag_a4` (adding sub-district), `gtag_a4l` (adding locality), `gtag_a4ls1` (adding sublocality 1, our standard neighborhood definition), down to `gtag_a4ls3e3`. Because each coarser tag is a literal prefix of the finer ones, the family of tags forms a tree: a coarse tag "resolves" into its children exactly at the field where the underlying API responses begin to diverge. Within the estimation sample of this paper, listings fall into 4,961 distinct `gtag_a4ls1` neighborhoods.

Neighborhood polygons. The second step converts each tag's point cloud into a polygon, and resolves overlaps so that the final map partitions claimed space into mutually exclusive (but not exhaustive) neighborhoods.

Step 1. Alphashapes. For every tag with at least three distinct coordinates, we compute the alphashape (a bounding polygon that contains a set of points, generalizing the notion of a convex hull to allow for a degree of concavity) of its points in projected coordinates (UTM 43N). The concavity parameter is set by the automatic optimizer of the Python `alphashape` library for each tag, tightening the set boundary to a single polygon that contains all of the tag's points. Tags with fewer than three points receive no polygon. Listings in unpolygonized tags retain the tag for fixed-effects purposes, but do not have a shape. Alphashapes of neighboring tags may overlap, as points of adjacent neighborhoods may interpenetrate along their boundary, and a parent's residual tag by construction surrounds its named children.

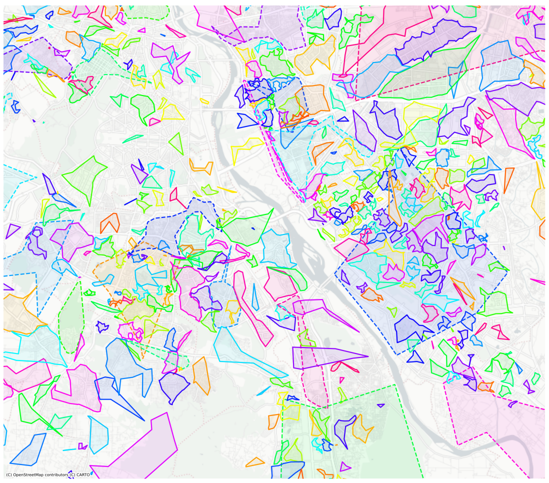
Step 2. Carving. We resolve overlaps by a mosaic-and-Voronoi space carving procedure. Each alphashape is first buffered by two meters, deliberately converting near-touching boundaries into explicit overlaps. The buffered and overlapping shapes are mosaicked, i.e., split into intersection sets such that each piece is claimed by a unique subset of alphashapes. Pieces claimed by a single tag are assigned to it directly. Each piece claimed by two or more tags is carved by a *constrained Voronoi* step: a Voronoi diagram is computed over the tagged points inside the piece, each cell of the diagram is clipped to the piece and assigned the tag of its nearest point, and cells sharing a tag are dissolved. Slivers of space that intersect no labeled shape are discarded. Finally all pieces are dissolved by tag, yielding one (possibly multi-part) polygon per tag. By construction the resulting polygons are pairwise disjoint; space far from any tagged point remains unclaimed.

Figure B.1 illustrates the output for the Delhi NCR. The top row shows a dense central area at the standard neighborhood resolution used in the paper (`a4ls1`). Panel (a) shows the raw alphashapes, with overlapping hulls, and panel (b) shows the same area after carving, with overlaps resolved. The bottom row shows the full metro area on the carved layer at two resolutions: panel (c) at `a4` (sub-districts) and panel (d) at `a4ls1`, the same tag tree read three levels deeper. Dashed outlines mark tags where the last branch in the tree is not specified.

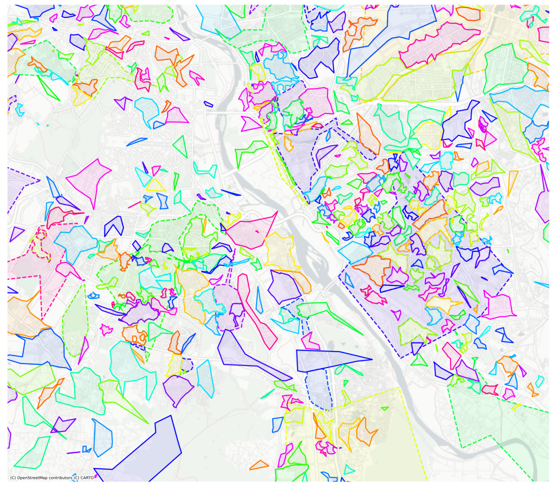
Neighborhood attributes are used as i) neighborhood identifiers (using only the tag tree, not the geometry) for neighborhod fixed effects, and ii) to attribute spatial features to neighborhood identifiers (using polygons), for instance in averaging Safetipin safety audits or street-light counts.

B3 Listings data from Bangladesh and Sri Lanka

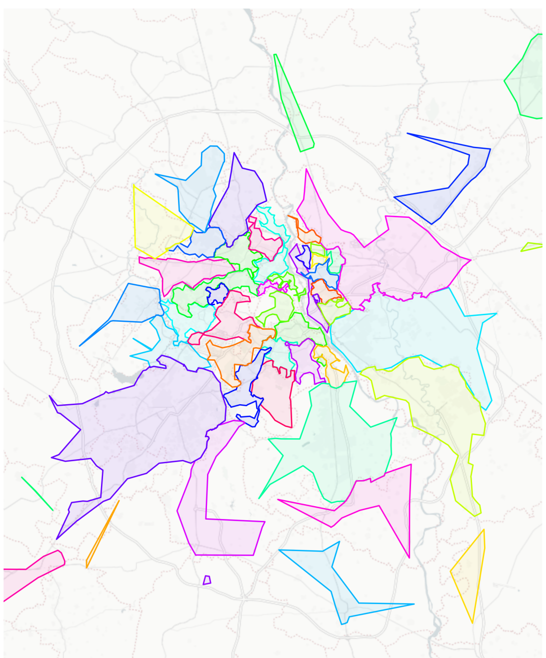
In addition to the platforms scraped in India, we also scraped data from platforms in Bangladesh and Sri Lanka, platforms B and I respectively. To create our samples, we



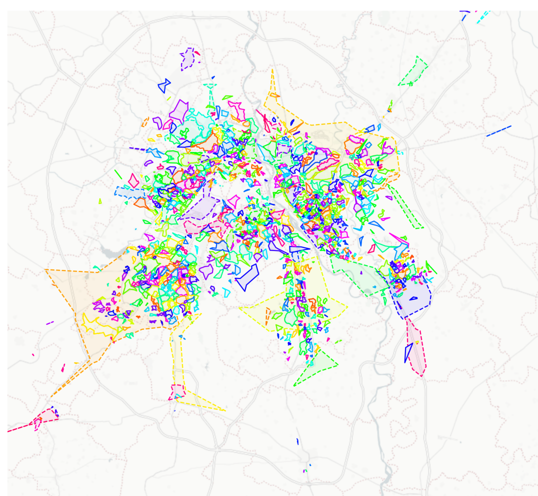
(a) Central Delhi, `a4ls1` alphashapes



(b) Central Delhi, `a4ls1` polygons



(c) Delhi NCR, `a4` (sub-district) polygons



(d) Delhi NCR, `a4ls1` polygons

Figure B.1: Neighborhood shapes from reverse-geocoded place tags, Delhi NCR.

kept only advertisements that were gender-classified and marketed as women-only or male-only.

Our samples include 4,381 advertisements for platform B, of which 65.62% were advertised for women and 34.38% for men, and 12,287 advertisements for platform I, of which 61.70% were advertised only for women and 38.30% for men. The period covered is from August 2021 to December 2024 for both platforms.

Of the sample for platform B, 87.51% is located in Dhaka, the capital city of Bangladesh. Our sample for platform I is mainly concentrated in Colombo, the capital of Sri Lanka (75.52% of the advertisements), followed by Gampaha (12.70% of the advertisements).

B4 Household Consumption and Expenditure Survey 2023-24

For the construction of the *Household Consumption Expenditure Survey (HCES) 2023–24* analytical dataset, we replicated and adapted the processing pipeline from the public GitHub repository *hces_2023* by Advait Moharir.[29] Specifically, we used the repository's scripts and workflow to import the raw microdata, harmonize variable names and codes, generate household and person identifiers, classify expenditu99re items, and produce analysis-ready intermediate files.

B5 Safety data

Table B5 reproduces the SafetiPin audit rubric: the nine parameters an auditor scores and the criteria for each score.

[29] https://github.com.mcas.ms/advaitmoharir/hces_2023/tree/main

Table B.2: SafetiPin Parameters

S.No.	Parameter	Score: 0	Score: 1	Score: 2	Score: 3
1	Light (Night)	**None**. No street or other lights.	**Little**. Can see lights, but barely reaches this spot.	**Enough**. Lighting is enough for clear visibility.	**Bright**. Whole area brightly lit.
2	Openness	**Not Open**. Many blind corners and no clear sightline.	**Partly Open**. Able to see a little ahead and around.	**Mostly Open**. Able to see in most directions.	**Completely Open**. Can see clearly in all directions.
3	Visibility	**No Eyes**. No windows or entrances (to shops or residences) or street vendors.	**Few Eyes**. Less than 5 windows or entrances or street vendors.	**More Eyes**. Less than 10 windows or entrances or street vendors.	**Highly Visible**. More than 10 windows or entrances or street vendors.
4	Crowd	**Deserted**. No one in sight.	**Few People**. Less than 10 people in sight.	**Some Crowd**. More than 10 people visible.	**Crowded**. Many people within touching distance.
5	Security	**None**. No private security or police visible.	**Minimal**. Some private security visible in surrounding area but not nearby.	**Moderate**. Private security within hailing distance.	**High**. Police within hailing distance.
6	Walk Path	**None**. No walking path available.	**Poor**. Path exists but in very bad condition.	**Fair**. Can walk but not run.	**Good**. Easy to walk fast or run.
7	Public Transport	**Unavailable**. No metro or bus stop, auto rickshaw or cycle rickshaw within 10 min walk.	**Distant**. Metro or bus stop, auto/cycle rickshaw within 10 min walk.	**Nearby**. Within 2–5 min walk.	**Very Close**. Within 2 min walk.
8	Gender Usage	**Not Diverse**. No one in sight, or only men.	**Somewhat Diverse**. Mostly men, very few women or children.	**Fairly Diverse**. Some women or children.	**Diverse**. Balanced or more women and children.
9	Feeling	**Frightening**. Will never venture here without escort.	**Uncomfortable**. Will avoid when possible.	**Acceptable**. Will choose other routes if available.	**Comfortable**. Feel safe even after dark.

Notes: This table is taken from Borker (2020) and shows an adapted version of the SafetiPin safety audit rubric that explains the options available to an app user when conducting an audit (Viswanath and Basu, 2015).

B6 Social norms

We use two sets of norm measures. Ancestral norms come from Giuliano and Nunn (2018), who match anthropological data from the Ethnographic Atlas (Murdock *et al.*, 1999) to the geographic distribution of language groups from Ethnologue (Lewis, 2009); each listing is assigned the ancestral characteristics of the ethnic group prevalent at its location. Contemporary norms come from the 2019–21 round of the National Family Health Survey (NFHS-5, the Indian implementation of the DHS), aggregated to the district level and matched to listings by district; two indicators are defined at the state level. Tables B.3 and B.4 define each variable.

Table B.3: Ancestral norm variables: definitions

Variable	Source	Construction
Premarital sex	EA078	Six categories as recorded: early marriage of females; insistence on virginity; prohibited but weakly censured; allowed (censured only if pregnancy); trial marriage, promiscuous relations prohibited; freely permitted.
Premarital sex strictly prohibited	EA078	$= 1$ if EA078 is early marriage of females, insistence on virginity or prohibited but weakly censured; $= 0$ if allowed (censured only if pregnancy)/ freely permitted.
Kinship descent	EA043	Patrilineal; Matrilineal; Mixed/Other (duolateral, quasi-lineages, ambilineal, bilateral, mixed).
Marriage mode	EA006	Recorded as bride price/wealth to bride's family, bride service, token bride price, gift exchange, sister exchange, absence of consideration, or dowry. $= 1$ for dowry, $= 0$ for bride price.
Male share of traditional tasks	EA044–EA054	Share of eleven subsistence tasks (metalworking, weaving, leatherworking, pottery, boat building, house construction, gathering, hunting, fishing, animal husbandry, agriculture) performed by "males only" or "male appreciably more," among tasks with defined gender participation. Ranges from 0 to 1.

Notes: EA codes refer to Ethnographic Atlas variables; category labels follow the Atlas. Constructed categorical variables assign Patrilineal = 1, Matrilineal = 2, Mixed/Other = 0.

Ancestral norms index. We construct an index of ancestral gender norms as the average of four standardized components, each signed so that larger values indicate more egalitarian norms: premarital sex freely permitted (rather than restricted), bride price (rather than dowry), matrilineal (rather than patrilineal) descent, and the male share of subsistence tasks (reversed, so a smaller male share corresponds to a larger index value). The resulting average is standardized.

Contemporary norms index. We constructed an analogous index of contemporary gender norms as the average of five standardized components, each signed so that larger values indicate greater female empowerment: son preference (reversed), female

Table B.4: Contemporary norm variables: definitions

Variable	Source	Level	Definition
Early adopter states	Hindu Succession Act reform	State	= 1 for Kerala, Andhra Pradesh, Tamil Nadu, Karnataka, and Maharashtra, which reformed gendered inheritance laws ahead of the national 2005 amendment.
Matrilineal states	Jayachandran and Pande (2017)	State	= 1 for Kerala, Assam, Manipur, Meghalaya, Mizoram, Nagaland, Sikkim, and Tripura.
Son preference	NFHS-5 (v627, v628)	District	Share of women whose ideal number of sons exceeds their ideal number of daughters.
Female employment	NFHS-5 (v714)	District	Share of women currently employed.
Female mobility	NFHS-5 (s930c)	District	Share of women who can go alone to places outside the village.

Notes: District-level NFHS measures are shares of women constructed from individual-level binary responses.

employment, female mobility, the early-adopter indicator, and the matrilineal indicator. The resulting average is standardized.

Appendix C Additional results

C1 Gender gaps in Bangladesh and Sri Lanka

Tables C.5 and C.6 present the coefficient of interest with progressively added controls and time fixed effects from columns 1 to 4, using the samples described in Appendix B3. The specification in column 4 includes the full set of controls, time and city fixed effects. Female-only accommodations charge approximately 7% more in monthly rent than male-only accommodations in platform B (Bangladesh) and 10% more in platform I (Sri Lanka).

Table C.5: Gender differential in rents: Bangladesh (Platform B)

	Log (Listing Price)			
	(1)	(2)	(3)	(4)
Advertised for only-females	0.064***	0.070***	0.071***	0.070***
	(0.013)	(0.012)	(0.011)	(0.011)
N	4377	4377	4377	4375
Avg Listing Price (Male-only, TK)	6943	6943	6943	6943
Time FE	X	X	X	X
Controls		X	X	X
Extended Controls			X	X
City FE				X

Notes: The table reports results from OLS regressions. The dependent variable in columns 1 through 6 is logarithm of the rent price. All regressions include time fixed effects. Controls include the common amenities between platform N and platform B: TV, WiFi, AC, power backup, geyser, parking, fridge, washing machine, gym, pool, balcony, lift and security guard. Extended controls are amenities that are only included in B and are the presence of cupboard, car parking and fire security. The sample for platform B includes 14 different cities. Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$.

Table C.6: Gender differential in rents: Sri Lanka (Platform I)

	Log (Listing Price)			
	(1)	(2)	(3)	(4)
Advertised for only-females	0.073***	0.109***	0.100***	0.100***
	(0.010)	(0.009)	(0.009)	(0.009)
N	12267	12267	12267	12266
Avg Listing Price (Male-only, RS)	14736	14736	14736	14736
Time FE	X	X	X	X
Controls		X	X	X
Extended Controls			X	X
City FE				X

Notes: The table reports results from OLS regressions. The dependent variable in columns 1 through 6 is logarithm of the rent price. All regressions include time fixed effects. Controls include the common amenities between platform N and platform I: TV, WiFi, AC, power backup, geyser, parking, fridge, washing machine, microwave, gym, pool, balcony, and lift. Extended controls are amenities that are only included in I and are the presence of cupboard, car parking and motor parking. The sample for platform I includes 21 different cities. Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.1$.

C2 Social norms

Tables C.7 and C.8 report the full regression results underlying Figure 3, for the ancestral and contemporary sets of norms respectively. Panel 1 reports the unconditional female-only coefficient and Panel 2 adds the interaction with each social norm.

Table C.7: Social Norms: ancestral characteristics

Panel 1: Unconditional	Log (Listing Price)			
	(1)	(2)	(3)	(4)
Advertised for only-females	0.069***	0.082***	0.066***	0.087***
	(0.005)	(0.005)	(0.006)	(0.004)
N	28,768	34,327	27,106	41,728
Avg Listing Price (Male-only, in INR)	7,901.777	7,800.536	7,768.074	7,632.590
Panel 2: Interacted with norm	Patrilineal descent	Premarital sex	Dowry	Male share of tasks
	(1)	(2)	(3)	(4)
Advertised for only-females	0.112***	0.021	0.055***	0.001
	(0.011)	(0.024)	(0.006)	(0.012)
Advertised for only-females x [norm]	-0.053***	0.064**	0.043***	0.117***
	(0.012)	(0.025)	(0.012)	(0.015)
N	28,768	34,327	27,106	41,728
Avg Listing Price (Male-only, in INR)	7,901.777	7,800.536	7,768.074	7,632.590
Time FE	X	X	X	X
Basic Features	X	X	X	X
Controls	X	X	X	X
Extended Controls	X	X	X	X
City FE	X	X	X	X

Notes: The table reports results from OLS regressions. The dependent variable is the logarithm of the rent price. All regressions include the full set of controls (basic features, amenities, and attributes), as well as time and city fixed effects. Panel 1 reports the unconditional coefficient on the female-only indicator, each column estimated on the non-missing-norm subsample used by that column in Panel 2. Panel 2 adds the interaction between female-only and the ancestral social norm from Giuliano and Nunn (2018) listed in that column: (1) patrilineal descent (vs. matrilineal); (2) premarital sex strictly restricted (vs. freely permitted); (3) dowry (vs. bride price); (4) male share of subsistence tasks (metalworking, weaving, leatherworking, pottery, construction, hunting, gathering, and agriculture; standardized, higher values indicate a larger male share). Robust standard errors in parentheses* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C3 Robustness

Table C.9: Robustness: Gender differential in rents, Platform O

	Log (Listing Price)					
	(1)	(2)	(3)	(4)	(5)	(6)
Advertised for only-females	0.024***	0.027***	0.025***	0.024***	0.064***	0.066***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
N	63785	63785	63785	63785	63785	63464
Avg Listing Price (Male-only, INR)	6005	6005	6005	6005	6005	6007
Time FE	X	X	X	X	X	X
Furnishing		X	X	X	X	X
Controls			X	X	X	X
Extended Controls				X	X	X
City FE					X	X
Neighborhood FE						X

Notes: The table reports results from OLS regressions on platform O, mirroring the specification in Table 3. The dependent variable in columns 1 through 6 is the logarithm of the rent price. All regressions include time fixed effects. Basic features control includes number of tenants sharing a room and indicators for whether the accommodation is furnished or semi-furnished. Controls include the common amenities between platforms N, M, and O: TV, WiFi, AC, food service, geyser, two- and four-wheeler parking, car parking, fridge, and washing machine. Extended controls add maid service, mess/meal service, and an indicator for proximity to a train/metro station. The sample includes 10 different cities; neighborhood fixed effects were defined using neighborhood tags and the sample includes 1,430 different neighborhoods. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C.8: Social Norms: contemporary indicators

Panel 1: Unconditional	Log (Listing Price)				
	(1)	(2)	(3)	(4)	(5)
Advertised for only-females	0.086***	0.086***	0.085***	0.085***	0.085***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
N	43,000	43,000	42,683	42,669	42,681
Avg Listing Price (Male-only, in INR)	7,554.487	7,554.487	7,566.856	7,567.295	7,566.856
Panel 2: Interacted with norm	Early adopters	Matrilineal states	Want more sons	Women employed	Women mobility
	(1)	(2)	(3)	(4)	(5)
Advertised for only-females	0.102***	0.085***	0.092***	0.096***	0.094***
	(0.006)	(0.004)	(0.006)	(0.005)	(0.005)
Advertised for only-females x [norm]	-0.030***	0.018	0.011	-0.031***	-0.017***
	(0.008)	(0.023)	(0.007)	(0.005)	(0.005)
N	43,000	43,000	42,683	42,669	42,681
Avg Listing Price (Male-only, in INR)	7,554.487	7,554.487	7,566.856	7,567.295	7,566.856
Time FE	X	X	X	X	X
Basic Features	X	X	X	X	X
Controls	X	X	X	X	X
Extended Controls	X	X	X	X	X
City FE	X	X	X	X	X

Notes: The table reports results from OLS regressions. The dependent variable is the logarithm of the rent price. All regressions include the full set of controls (basic features, amenities, and attributes), as well as time and city fixed effects. Panel 1 reports the unconditional coefficient on the female-only indicator, each column estimated on the non-missing-norm subsample used by that column in Panel 2. Panel 2 adds the interaction between female-only and the contemporary social norm listed in that column: (1) indicator for early-adopter states of the Hindu Succession Act reform; (2) indicator for matrilineal states (Jayachandran and Pande, 2017); (3) son preference; (4) female employment; (5) freedom of physical mobility (columns 3–5: urban DHS 2019–21, district level, standardized). Robust standard errors in parentheses* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.10: Robustness: Gender differential in rents including unisex listings

	Log (Listing Price)					
Platform N	(1)	(2)	(3)	(4)	(5)	(6)
Advertised for only-females	0.039***	0.092***	0.078***	0.086***	0.078***	0.074***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Advertised for both genders (unisex)	0.242***	0.213***	0.190***	0.166***	0.161***	0.150***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
N	65664	65553	63807	63796	63796	63612
Avg Listing Price (Male-only, INR)	7551	7552	7590	7590	7590	7589
R2	0.051	0.273	0.446	0.490	0.528	0.544
Platform M						
Advertised for only-females	0.063***	0.088***	0.081***	0.081***	0.068***	0.070***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Advertised for both genders (unisex)	0.172***	0.147***	0.119***	0.081***	0.049***	0.054***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
N	92260	92186	91114	87639	87639	87639
Avg Listing Price (Male-only, INR)	8042	8044	8059	8166	8166	8166
R2	0.108	0.229	0.390	0.519	0.541	0.545
Time FE	X	X	X	X	X	X
City FE		X	X	X	X	X
Neighborhood FE			X	X	X	X
Basic Features				X	X	X
Controls					X	X
Extended Controls						X

Notes: The table reports results from OLS regressions mirroring the specification in Table 3, but instead of dropping listings advertised for both genders, this table keeps them as a third category. Male-only listings are the omitted baseline; the two reported rows are the coefficients on indicators for female-only and unisex (both-gender) listings, estimated jointly in the same regression. The dependent variable in columns 1 through 6 is the logarithm of the rent price. All regressions include time fixed effects. Basic features, controls and extended controls are as defined in Table 3. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table C.11: Social Norms: ancestral characteristics (non-metro cities)

Panel 1: Unconditional	Log (Listing Price)			
	(1)	(2)	(3)	(4)
Advertised for only-females	0.056***	0.061***	0.056***	0.067***
	(0.008)	(0.007)	(0.008)	(0.007)
N	12,948	14,747	12,662	16,673
Avg Listing Price (Male-only, in INR)	5,965.295	6,070.937	6,064.607	5,928.739
Panel 2: Interacted with norm	Patrilineal descent	Premarital sex	Dowry	Male share of tasks
	(1)	(2)	(3)	(4)
Advertised for only-females	0.108***	0.021	0.048***	-0.002
	(0.022)	(0.024)	(0.009)	(0.017)
Advertised for only-females x [norm]	-0.057**	0.045*	0.050**	0.106***
	(0.024)	(0.025)	(0.021)	(0.025)
N	12,948	14,747	12,662	16,673
Avg Listing Price (Male-only, in INR)	5,965.295	6,070.937	6,064.607	5,928.739
Time FE	X	X	X	X
Basic Features	X	X	X	X
Controls	X	X	X	X
Extended Controls	X	X	X	X
City FE	X	X	X	X

Notes: Robustness version of Table C.7, dropping listings in the six largest metropolitan areas (Delhi, Kolkata, Chennai, Mumbai, Bangalore, Hyderabad), where gender norms are less binding. Same specifications and controls otherwise. Robust standard errors in parentheses* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.12: Social Norms: contemporary indicators (non-metro cities)

Panel 1: Unconditional	Log (Listing Price)				
	(1)	(2)	(3)	(4)	(5)
Advertised for only-females	0.066***	0.066***	0.067***	0.067***	0.066***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
N	17,354	17,354	17,302	17,288	17,300
Avg Listing Price (Male-only, in INR)	5,906.092	5,906.092	5,910.647	5,910.607	5,910.647
Panel 2: Interacted with norm	Early adopters	Matrilineal states	Want more sons	Women employed	Women mobility
	(1)	(2)	(3)	(4)	(5)
Advertised for only-females	0.078***	0.065***	0.070***	0.079***	0.068***
	(0.009)	(0.007)	(0.008)	(0.008)	(0.007)
Advertised for only-females x [norm]	-0.027**	0.024	0.009	-0.032***	-0.005
	(0.013)	(0.023)	(0.010)	(0.009)	(0.008)
N	17,354	17,354	17,302	17,288	17,300
Avg Listing Price (Male-only, in INR)	5,906.092	5,906.092	5,910.647	5,910.607	5,910.647
Time FE	X	X	X	X	X
Basic Features	X	X	X	X	X
Controls	X	X	X	X	X
Extended Controls	X	X	X	X	X
City FE	X	X	X	X	X

Notes: Robustness version of Table C.8, dropping listings in the six largest metropolitan areas (Delhi, Kolkata, Chennai, Mumbai, Bangalore, Hyderabad), where gender norms are less binding. Same specifications and controls otherwise. Robust standard errors in parentheses* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$