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How Do Platform-Based Trust Signals Shape Airbnb Prices Across European Cities?

Platform Tabanlı Güven Sinyalleri Avrupa Şehirlerinde Airbnb Fiyatlarını Nasıl Şekillendiriyor?

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ABSTRACT

This study examines how trust signals generated by tourism platforms are reflected in prices within peer-to-peer accommodation markets. Trust signals including cleanliness ratings, guest satisfaction scores, and platform-designated quality certifications serve as digital reputation indicators that help guests evaluate service quality in the absence of traditional hotel brand guarantees. Using a dataset of 51,448 Airbnb listings across ten major European cities, hedonic pricing models and machine learning methods were employed to estimate the marginal price associations of these trust dimensions. The results revealed that cleanliness functions as the most economically significant trust signal, being associated with an average price premium of 3.64% per standard deviation increase. Overall satisfaction shows minimal pricing impact once specific quality dimensions are controlled for. Trust premiums vary substantially by accommodation format. Private rooms exhibit the highest cleanliness premium at 6.29%, while entire homes show a premium of 2.69%, reflecting differential perceived hygiene risks across room types. Cross-city analysis reveals considerable geographic heterogeneity, with cleanliness premiums ranging from 1.3% in Lisbon to 5.2% in Athens, indicating that trust monetization is associated with local market conditions and competitive dynamics. Machine learning analysis confirms that trust signals rank among the most important determinants of listing prices, outpacing operational attributes but lagging behind location and structural characteristics. These findings advance understanding of how digital reputation systems are associated with economic value in platform markets and demonstrate that detailed quality signals are associated with more efficient price formation than aggregate ratings.

Keywords: Airbnb, hedonic pricing, peer-to-peer markets, sharing economy, tourism platforms, trust signals

Öz

Bu çalışma, turistik platformlar tarafından oluşturulan güven sinyallerinin, kişiler arası konaklama pazarlarında fiyatlara nasıl yansıtıldığını incelemektedir. On büyük Avrupa şehrindeki 51.448 Airbnb ilanından oluşan bir veri seti kullanarak, temizlik derecelendirmelerinin, konuk memnuniyet puanlarının ve Süper Ev Sahibi statüsünün marjinal fiyat ilişkilerini tahmin etmek için hedonik fiyatlandırma modelleri ve makine öğrenme yöntemleri kullanılmıştır. Sonuçlar, temizliğin en ekonomik açıdan önemli güven sinyali olarak işlev gördüğünü ve standart sapma artışı başına ortalama %3,64'lük bir fiyat primi ile ilişkili olduğunu, genel memnuniyetin ise belirli kalite boyutları kontrol edildiğinde minimum fiyatlandırma etkisi gösterdiğini ortaya koymaktadır. Güven primleri, konaklama formatına göre önemli ölçüde değişmekte olup, özel odalar %6,29 ile en yüksek temizlik primine sahipken, tüm evler için bu oran %2,69'dur; bu da oda tipleri arasında algılanan hijyen risklerindeki farklılıkları yansıtmaktadır. Şehirlerarası analiz, temizlik primlerinin Lizbon'da %1,3'ten Atina'da %5,2'ye kadar değiştiğini ve güvenin paraya dönüştürülmesinin yerel pazar koşullarına ve rekabet dinamikleriyle ilişkili olduğunu gösteren önemli coğrafi heterojenliği ortaya koymaktadır. Rastgele Orman algoritması güven sinyallerinin, operasyonel özelliklerin üzerinde, ancak konum ve yapısal özelliklerin gerisinde kalarak listeleme fiyatlarının en önemli belirleyicileri arasında yer aldığını doğrulamaktadır. Bu bulgular, dijital itibar sistemlerinin platform pazarlarında ekonomik değerle nasıl ilişkili olduğuna dair anlayışı geliştirmekte ve ayrıntılı kalite sinyallerinin, toplu derecelendirmelere kıyasla daha verimli fiyat oluşumuyla ilişkili olduğunu göstermektedir.

Anahtar Kelimeler: Airbnb, hedonik fiyatlandırma, kişiler arası pazarlar, paylaşım ekonomisi, turistik platformlar, güven sinyalleri

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1. INTRODUCTION

The expansion of digital platforms has fundamentally restructured traditional markets by enabling direct peer-to-peer transactions between previously disconnected parties (Perez-Sanchez et al., 2018). In accommodation markets, this transformation is epitomized by Airbnb, which has grown from a marginal alternative to a dominant force in urban tourism and short-term accommodation (Adamiak, 2020). By 2024, the platform is effectively disintermediating the hospitality sector and reshaping competitive dynamics in metropolitan housing markets, facilitating millions of transactions annually in over 220 countries (Garay-Tamajón et al., 2022).

Central to the functioning of these peer-to-peer platforms is the mitigation of information asymmetry (Hall et al., 2023). Although hotel chains embed quality signals institutionally through brand reputation and regulatory compliance, a substantial body of evidence shows that hotels are themselves strongly affected by online reviews and ratings on platforms such as TripAdvisor, online travel agencies, and Google, with online reputation linked to occupancy and revenue. Institutional and reputational signals are therefore better understood as a continuum rather than a dichotomy. What distinguishes platform-mediated accommodation is that transactions occur between strangers with minimal ex-ante information about service quality and without the institutional guarantees that, in the hotel sector, operate alongside online reputation (Godovykh et al., 2023). Guests must rely on digitally mediated signals to assess the credibility and trustworthiness of hosts they have never met. Platforms address this fundamental coordination problem by constructing elaborate reputation systems that aggregate past user experiences into quantifiable trust indicators (Qiu et al., 2018).

While existing research has established that reputation matters in peer-to-peer markets, the specific mechanisms through which different trust signals are capitalized into prices remain insufficiently understood (Einav et al., 2016). Prior studies have examined aggregate rating effects, but the heterogeneous valuation of distinct trust dimensions across different market segments and urban contexts has received limited empirical attention (Berg et al., 2020; Einav et al., 2016; Teubner et al., 2017). This gap is particularly consequential given that platform operators increasingly differentiate their reputation architectures by introducing granular quality metrics alongside binary status badges, yet the relative pricing power of these varied signals remains theoretically and empirically ambiguous.

This study addresses these gaps by investigating how platform-generated trust signals are monetized in European Airbnb markets, with particular emphasis on cleanliness ratings and Superhost status as distinct mechanisms for quality signalling. The analysis contributes to the literature in three primary ways. First, it decomposes the trust premium into specific dimensions, demonstrating that cleanliness operates as a more precise and economically significant signal than generalized satisfaction ratings. Second, it reveals substantial heterogeneity in trust monetization across accommodation formats, showing that the value of cleanliness varies systematically by room type in ways that reflect underlying risk perceptions. Third, it documents cross-city variation in trust premiums, providing evidence that the economic significance of platform reputation differs across urban markets with distinct competitive and regulatory characteristics.

The empirical analysis draws on a multi-city dataset encompassing 51,448 Airbnb listings across ten major European cities: Amsterdam, Athens, Barcelona, Berlin, Budapest, Lisbon, London, Paris, Rome, and Vienna. Using hedonic pricing models with city fixed effects and machine learning robustness checks, the study estimates the marginal price effects of platform trust signals while controlling for property characteristics, spatial location, and temporal demand variation.

The investigation is organized around five interrelated research questions.

- After checking room type, property features, and location, to what extent do platform trust signals, particularly cleanliness ratings and Super Host status, increase Airbnb listing prices in European cities?
- Are trust premiums uniform across accommodation formats, or do they vary by room type, distinguishing between entire homes, private rooms, and shared rooms?
- How does the monetization of trust differ across cities, revealing whether European urban markets vary systematically in the size of the cleanliness-based price premium?
- Relative to classic hedonic determinants such as location and unit size, how important are trust signals for explaining and predicting prices in platform markets?
- Do trust signals act as substitutes or complements to spatial convenience, meaning does the trust premium strengthen or weaken as listings become less centrally located?

2. LITERATURE REVIEW

The emergence of peer-to-peer platforms has created new market architectures that fundamentally differ from traditional intermediated exchanges (Abrate & Viglia, 2017). Platform-mediated transactions occur between previously disconnected strangers who lack institutional guarantees of quality or reliability, generating severe information asymmetries that could theoretically impede market formation (Wells et al., 2011). Economic theory suggests that in the absence of credible quality signals, adverse selection may drive high-quality providers from the market, leaving only low-quality offerings and causing market failure (Karlan et al., 2016). Platform operators address this coordination problem by constructing digital reputation systems that aggregate user feedback into quantifiable trust indicators, effectively substituting algorithmic verification for institutional certification (Suali et al., 2024).

Theoretical studies on reputation mechanisms demonstrate that repeated interaction and public feedback can sustain cooperative equilibria in settings where formal contracts are costly or unenforceable (José Ganuza et al., 2016). When transaction histories are observable and reputational consequences persist across exchanges, strategic actors have incentives to maintain quality standards even in anonymous digital markets (Przepiorka et al., 2017). Empirical research confirms that reputation systems generate measurable economic value across diverse platform contexts, including e-commerce marketplaces, ride-sharing services, and freelance labor platforms (Batool et al., 2020). Sellers with higher ratings consistently command price premiums, achieve faster transaction velocities, and maintain larger market shares than lower-rated competitors, validating the theoretical proposition that reputation serves as an economic asset (Moreno & Terwiesch, 2014).

It is necessary to clarify what is meant by a “trust signal” in this study, since trust, perceived service quality, hygiene, and platform reputation are related but conceptually distinct constructs. Following the signalling and reputation literature, this study treats trust as the guest’s willingness to transact under conditions of uncertainty about an unobservable host, and treats platform-generated metrics as observable signals that reduce that uncertainty. Within this framework, cleanliness ratings, overall guest satisfaction, and Superhost status are interpreted as trust signals not because they are equivalent to trust itself, but because each conveys credible, peer-validated information that lowers perceived transaction risk. These signals are not interchangeable: cleanliness may simultaneously operate as a service-quality indicator, a professionalism cue, and a hygiene-related risk-reduction mechanism; overall satisfaction is a composite evaluation aggregating many dimensions; and Superhost status is a platform-conferred status badge. The study therefore does not claim that these variables measure a single latent trust construct. Rather, it examines how each signal with its distinct informational content is reflected in prices, and interprets differences in their price associations as

evidence about which kinds of signals are most diagnostic for guests rather than as a direct measurement of trust, service quality, or hygiene as such.

Within accommodation markets specifically, hedonic pricing models provide the primary analytical framework for decomposing listing prices into component attributes (Chattopadhyay & Mitra, 2020). The hedonic approach, formalized by Rosen and extensively applied to housing markets, conceptualizes goods as bundles of characteristics with implicit prices revealed through market transactions (Pawlicz & Napierala, 2017). Early hedonic studies of hotel pricing documented that location, property amenities, chain affiliation, and star ratings explain substantial price variation, with proximity to central business districts and tourist attractions commanding consistent premiums (Chattopadhyay & Mitra, 2020). The rise of Airbnb and similar platforms has extended this framework to peer-to-peer accommodation, where the absence of standardized quality certifications makes reputation signals particularly salient (Adamiak et al., 2019).

Empirical investigations of Airbnb pricing have established that overall ratings and review volumes positively influence listing prices across multiple geographic markets (Tong & Gunter, 2022; Teubner et al., 2017). Studies examining U.S. cities, European capitals, and Asian metropolitan areas consistently find that higher aggregate ratings translate into price premiums, with effect sizes typically ranging from two to eight percent depending on market characteristics and model specifications (Tong & Gunter, 2022; Voltes-Dorta & Inchausti-Sintes, 2021). Host characteristics including Superhost designation and response rates also exhibit positive pricing effects, suggesting that platform-certified quality badges convey information beyond numeric ratings (Sipic, 2017). Location remains the dominant price determinant in most analyses, consistent with urban economic theory emphasizing spatial accessibility and proximity to amenities (Bruno et al., 2016).

However, existing research exhibits three notable limitations that this study addresses. First, prior work has primarily examined aggregate overall ratings rather than decomposing reputation into specific quality dimensions such as cleanliness, communication, or accuracy (Voltes-Dorta & Inchausti-Sintes, 2021). This aggregation obscures which trust signals carry the greatest informational value and pricing power, limiting both theoretical understanding and practical guidance for hosts seeking to optimize quality investments. Second, the heterogeneity of trust premiums across accommodation formats has received limited systematic attention. Most studies pool entire homes, private rooms, and shared accommodations despite theoretical reasons to expect differential valuation of trust signals across segments characterized by varying privacy levels and host-guest proximity (Ding et al., 2023). Third, cross-market variation in trust monetization remains underexplored. While some studies document geographic heterogeneity in overall price levels, the extent to which trust premiums themselves vary across cities with different competitive dynamics, regulatory environments, and tourism characteristics has not been comprehensively examined (Gunter & Wöber, 2022; Romão et al., 2017).

This study contributes to the literature by providing a systematic comparison of granular trust signals across European markets, providing evidence that cleanliness is associated with larger and more consistent price premiums than generalized satisfaction ratings. The analysis of trust premium heterogeneity by room type reveals that quality signal valuation depends critically on structural accommodation characteristics and perceived risk exposure. The cross-city estimation strategy documents substantial geographic variation in trust monetization, suggesting that platform reputation effects are contextually determined rather than uniformly applicable across markets. By combining hedonic regression with machine learning robustness checks, the study also advances methodological practice in platform market research, demonstrating that trust effects emerge consistently across parametric and non-parametric modelling approaches. It is important to delineate the incremental contribution of this study relative to prior cross-city European Airbnb research, in particular the spatial

hedonic analysis of the same ten European cities by Gyódi and Nawaro (2021), from which the underlying listing data are drawn. That study focuses primarily on the role of location and neighbourhood attractiveness as price drivers and treats reputation variables largely as controls. The present study differs in its analytical emphasis rather than in its data: it reframes platform reputation variables as distinct trust signals, decomposes the reputation premium into specific dimensions, and examines the systematic variation of trust premiums across room types and cities, which the earlier location-centred analyses did not address. The contribution is therefore best understood as a conceptual and analytical extension of, rather than a replacement for, the established European Airbnb hedonic literature. These contributions deepen understanding of how digital reputation systems are associated with economic value in peer-to-peer markets and provide actionable insights for platform design, host strategy, and regulatory policy.

3. METHOD

3.1. Research Design and Data Sources

This study employs a cross-sectional hedonic pricing framework to estimate the marginal price associations of platform-generated trust signals in peer-to-peer accommodation markets. The empirical analysis draws on Airbnb listings from ten major European cities: Amsterdam, Athens, Barcelona, Berlin, Budapest, Lisbon, London, Paris, Rome, and Vienna, selected to capture variation in market maturity, regulatory environments, and tourism intensity. These ten cities are not a convenience sample but a fixed, pre-existing set of major European tourism destinations that span a wide range along three dimensions relevant to trust monetization: market maturity (e.g., long-established markets such as Paris and London versus more recently regulated markets such as Athens and Budapest), short-term-rental regulatory stringency (ranging from highly restrictive regimes such as Berlin and Amsterdam to comparatively permissive ones), and tourism intensity and price level (from high-price, supply-constrained markets such as Amsterdam to lower-price, high-volume markets such as Budapest and Athens). The descriptive cross-city differences in price levels reported in Section 4.1 provide empirical confirmation that the selected cities do in fact differ substantially along these dimensions. Because the city set is fixed rather than sampled, the analysis is not intended to support inference to a broader population of cities, and the cross-city comparisons should be read as descriptive of these ten markets.

Data were collected for weekdays and weekends, with weekend observations constituting approximately 51% of the sample. After trimming the upper 0.5% of the price distribution to mitigate extreme values and data anomalies, the final analytical sample consists of 51,448 listings. To improve transparency and replicability, the data provenance is described in detail here. The listing data are drawn from the publicly available multi-city European Airbnb dataset compiled and released by Gyódi and Nawaro (2021), which provides, for each of the ten cities, separate files for weekday and weekend offers together with the standardized variables used in this study (realSum, room type, person capacity, Superhost status, multi- and business-host indicators, cleanliness rating, guest satisfaction, bedrooms, and distance measures). The data therefore represent a cross-sectional snapshot rather than a panel, and the “weekday” and “weekend” designations correspond to the two collection files provided in that source rather than to repeated observations of the same listing over time. Because a given property can appear once in the weekday file and once in the weekend file, the same physical listing may contribute more than one observation; this non-independence is one motivation for clustering standard errors and is discussed further among the study’s limitations. The trimming threshold of the upper 0.5% was chosen to remove implausible price outliers (e.g., data-entry artefacts and ultra-luxury listings far outside the typical short-term-rental range) while retaining virtually all of the substantive price distribution; results are not sensitive to small changes in this threshold. The

number of observations contributing from each city is reported in Table 1, allowing readers to assess uneven sampling intensity across markets.

Table 1. Distribution of observations by city after trimming

City	Number of observations	Share of sample (%)
Amsterdam	2,069	4.02
Athens	5,254	10.21
Barcelona	2,819	5.48
Berlin	2,472	4.80
Budapest	4,002	7.78
Lisbon	5,734	11.15
London	9,943	19.33
Paris	6,654	12.93
Rome	8,982	17.46
Vienna	3,519	6.84
Total	**51,448**	**100.00**

3.2. Variable Operationalization

Dependent Variable: The listing price (realSum) represents the accommodation cost inclusive of cleaning fees and service charges. Prices are log-transformed (ln_price) to stabilize variance, enable percentage interpretation of coefficients, and improve residual distribution normality. The use of the natural logarithm, rather than an untransformed, square-root, or base-10 specification, follows standard practice in the hedonic accommodation-pricing literature (Wang & Nicolau, 2017; Gyódi & Nawaro, 2021) and is preferred for substantive rather than arbitrary reasons. Accommodation prices are right-skewed and approximately log-normal. The natural-log transformation therefore renders the distribution close to symmetric, as confirmed in Figures 1 and 2, and satisfies the normality assumptions underlying ordinary least squares more closely than a square-root transformation. Furthermore, in a semi-logarithmic specification, the estimated coefficients can be directly interpreted as approximate percentage changes in price, which is the economically meaningful quantity for a trust premium. The natural logarithm, as opposed to the base-10 logarithm, yields coefficients that map onto the conventional elasticity and semi-elasticity interpretations used throughout the hedonic literature, ensuring comparability with prior studies.

Platform Trust Signals: Three reputation-based indicators are examined. Cleanliness rating is measured on a continuous zero to ten scale, reflecting aggregated guest evaluations of hygiene standards. Overall guest satisfaction is measured on a zero to one hundred scale, capturing composite quality evaluation across multiple dimensions. Superhost status is a binary indicator capturing Airbnb's elite designation awarded based on high response rates, minimal cancellations, and consistent positive reviews. Cleanliness and satisfaction scores are standardized to z-scores to facilitate direct effect size comparison.

Property Characteristics: Control variables include room type (entire home/apartment as reference category, private room, shared room), person capacity, number of bedrooms, multi-unit listing status, and business-ready designation. Capacity and bedroom counts are log-transformed to reflect diminishing marginal returns.

Spatial Location: Distance to city center and distance to nearest metro station are measured in kilometers and transformed as log(1+distance) to accommodate non-linear spatial price gradients. Geographic coordinates are incorporated in machine learning analyses for fine-grained spatial modeling.

Temporal and Fixed Effects: A weekend indicator captures demand variation, while city fixed effects absorb unobserved heterogeneity across urban markets including regulatory stringency, tourism intensity, and market structure.

3.3. Empirical Strategy

The baseline hedonic specification is:

$$\ln(\text{Price}_{ic}) = \alpha + \mathbf{X}_{ic}\boldsymbol{\beta} + \mathbf{T}_{ic}\boldsymbol{\gamma} + \delta_c + \varepsilon_{ic} \quad (1)$$

where $\mathbf{X}_{ic}$represents property and location attributes, $\mathbf{T}_{ic}$captures trust signals, and $\delta_c$are city fixed effects. Standard errors are clustered at the city level.

Three nested models are estimated. Model 1 includes property characteristics, location variables, temporal controls, and city fixed effects. Model 2 adds platform trust signals, with the incremental R^2 quantifying variance explained by reputation metrics. Model 3 introduces Trust × Room Type interactions to examine whether trust premiums vary across accommodation formats, and Trust × Distance interactions to test whether trust signals act as substitutes or complements to spatial centrality.

3.4. City-Specific and Machine Learning Analyses

Separate hedonic regressions for each city examine geographic heterogeneity in trust monetization. A Random Forest regression model trained on eighty percent of the data with twenty percent holdout assesses out-of-sample predictive performance and generates feature importance rankings using mean decrease in impurity based on reduction in squared error, validating findings across parametric and non-parametric approaches.

4. FINDINGS

4.1. Sample Characteristics and Price Distributions

Table 2 presents descriptive statistics for the pooled analytical sample of 51,448 Airbnb listings across ten European cities. The average listing price is €266.46, substantially higher than the median of €210.37, indicating considerable right skewness in the empirical price distribution. This asymmetry reflects the presence of luxury and high-capacity units in the upper tail, a characteristic feature of platform accommodation markets where pricing is less constrained by institutional standardization than in traditional hotel sectors.

Table 2. Descriptive statistics

Variable	Mean	SD	Min	Median	Max
Price (realSum)	266.46	185.08	34.78	210.37	1494.63
Log price (ln_price)	5.41	0.57	3.55	5.35	7.31
Person capacity	3.16	1.29	2	3	6
Bedrooms	1.15	0.62	0	1	10
Distance to center (km)	3.19	2.40	0.02	2.61	25.28
Distance to metro (km)	0.68	0.86	0.00	0.41	14.27
Cleanliness rating	9.39	0.95	2	10	10
Guest satisfaction	92.62	8.94	20	95	100

Listings in the sample typically accommodate three guests and contain one bedroom, reflecting the predominance of small-to-moderate urban units characteristic of European metropolitan housing stocks. The average distance to city center is 3.19 kilometres, with a median of 2.61 kilometres, suggesting that the sample captures both centrally located and moderately peripheral properties.

Metro accessibility is generally strong, with listings located an average of 680 meters from the nearest station.

Platform trust metrics exhibit relatively high mean values but limited variance. The average cleanliness rating is 9.39 on a 10-point scale, with a median of 10, indicating ceiling effects common in online reputation systems where only exceptionally negative experiences generate ratings substantially below the maximum. Similarly, guest satisfaction averages 92.62 out of 100, with a median of 95. Despite this restricted range, the standard deviations of 0.95 and 8.94 respectively suggest sufficient variation to identify pricing effects, particularly given the large sample size.

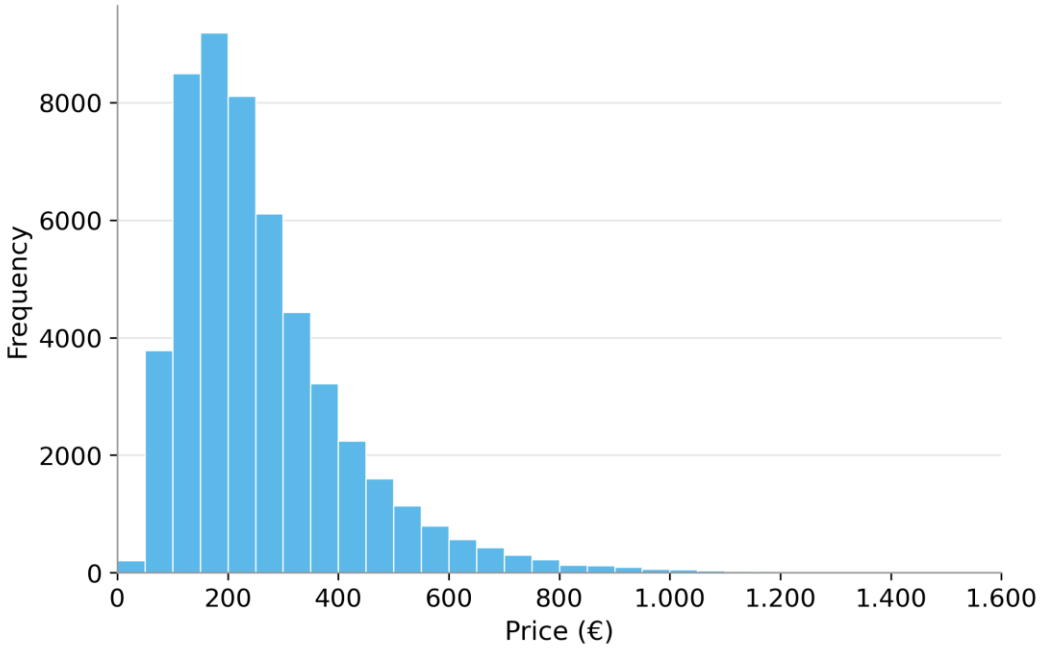


Figure 1. Price distribution (levels)

Figure 1 displays the trimmed price distribution in levels, confirming substantial positive skewness. The distribution exhibits a pronounced right tail extending beyond €1,000 per night, with the majority of listings concentrated between €100 and €400. Figure 2 demonstrates that the log-transformed price distribution approximates symmetry and approaches normality, validating the log-linear hedonic specification and supporting the efficiency of ordinary least squares estimation.

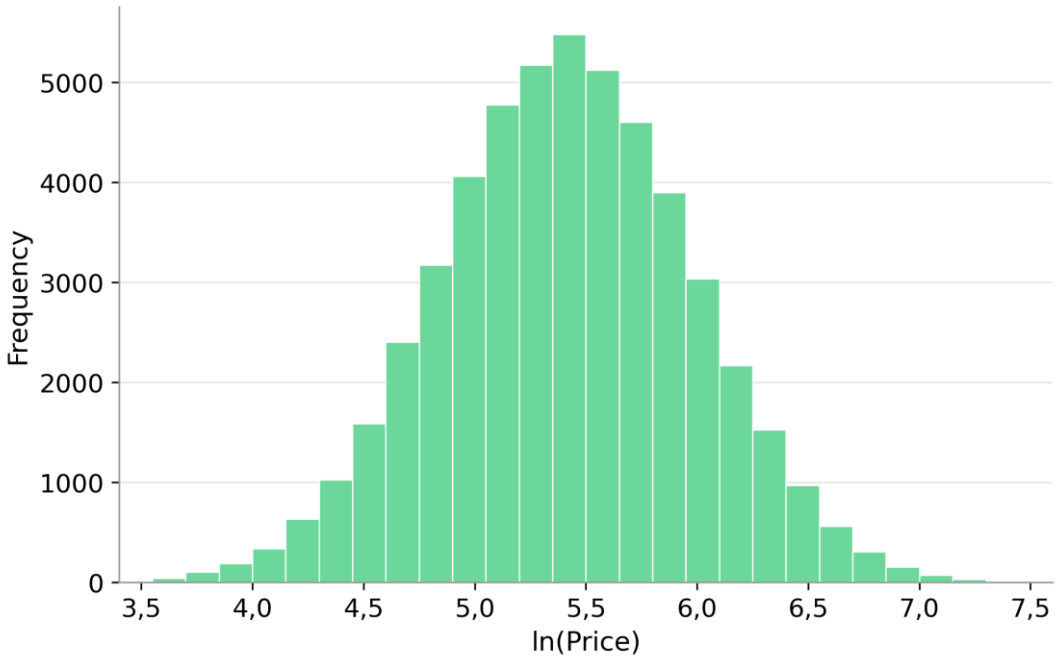


Figure 2. Log-transformed price distribution

Cross-city price variation is substantial and economically meaningful (Figure 3). Amsterdam commands the highest median price at €449, followed by Paris at €315, reflecting these cities' positions as premium tourism destinations with constrained short-term rental supply. In contrast, Athens and Budapest exhibit median prices of €128 and €153 respectively, consistent with lower purchasing power parity and less intensive international tourism demand. This pronounced heterogeneity underscores the necessity of city fixed effects to prevent cross-market differences from confounding the estimation of trust premiums.

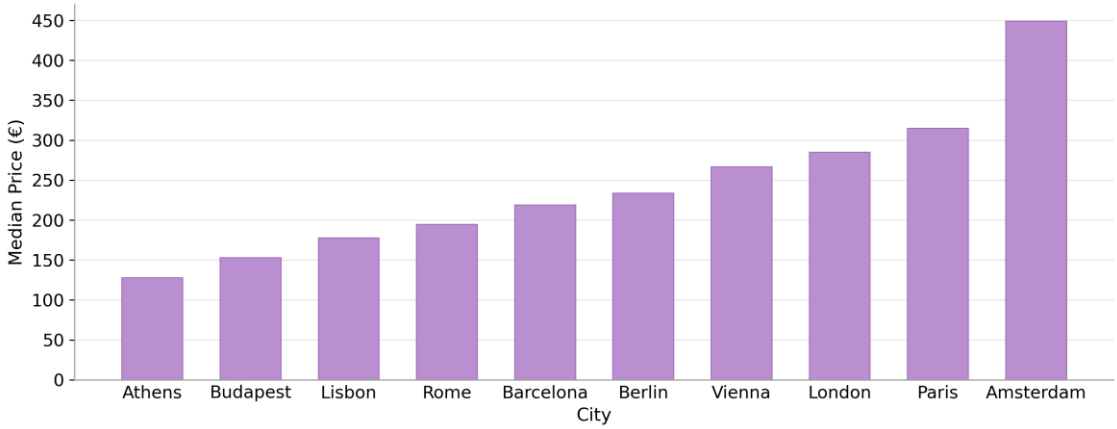


Figure 3. Median listing prices across European cities

4.2. Baseline Hedonic Pricing Model

Table 3 presents results from the sequential estimation strategy. Model 1 establishes the baseline hedonic pricing relationship, incorporating property characteristics, location variables, temporal controls, and city fixed effects. The model explains 64.4% of observed price variation, indicating strong explanatory power from traditional hedonic determinants alone.

Table 3. Hedonic pricing models

Variables	M1 Baseline	M2 + Trust	M3 Interactions
Log capacity	0.409***	0.415***	0.415***
Log bedrooms	0.267***	0.260***	0.261***
Log distance to center	−0.249***	−0.248***	−0.249***
Log distance to metro	n.s.	n.s.	n.s.
Weekend	0.029**	0.029**	0.029**
Superhost	0.047***	0.023*	0.021*
Cleanliness (z)	---	0.036***	0.027
Guest satisfaction (z)	---	0.008	0.036
City fixed effects	Yes	Yes	Yes
R^2	0.644	0.649	0.650
N	51,448	51,448	51,448

Note. Standard errors are clustered at the city level. *** $p < .001$, ** $p < .01$, * $p < .05$.

The results confirm expected relationships between property attributes and listing prices. A one-unit increase in log capacity is associated with a 40.9% price premium ($p < .001$), indicating that larger units command substantial premiums even after controlling for bedroom count. Each additional bedroom increases prices by approximately 26.7% ($p < .001$), reflecting the value guests place on privacy and spatial separation. These estimates align with prior hedonic studies of accommodation markets and demonstrate diminishing marginal returns to size, as evidenced by the log transformation dampening the effect of additional capacity at higher levels.

Spatial location exerts powerful effects on pricing. Distance to city center shows a strong negative relationship, with each unit increase in log distance associated with a 24.9% price reduction ($p < .001$). This centrality premium reflects the concentration of tourist attractions, commercial amenities, and cultural sites in urban cores, consistent with monocentric city models and bid-rent theoretical frameworks. Interestingly, distance to metro stations does not exhibit a statistically significant independent effect once centrality is controlled, suggesting that proximity to public transportation may be capitalized primarily through its correlation with central location rather than as a distinct amenity.

Temporal demand variation is captured by the weekend indicator, which shows a modest but statistically significant 2.9% price premium ($p < .01$). This differential likely reflects increased leisure travel demand during weekends relative to midweek business and budget travel.

Even in the baseline model, Superhost status demonstrates a significant price effect of 4.7% ($p < .001$), providing preliminary evidence that platform-certified quality signals are valued by guests. However, this coefficient likely conflates both trust signaling and unobserved quality differences correlated with Superhost designation, making it essential to control for explicit quality metrics in subsequent specifications.

4.3. The Trust Premium: Cleanliness and Platform Reputation

Model 2 introduces platform trust signals, resulting in a modest but statistically significant improvement in explanatory power ($\Delta R^2 = 0.005$). While this increment appears small in absolute terms, it represents meaningful additional variance explained beyond the already comprehensive set of property and location controls, and translates into economically significant price differentials given the sample size and price distributions.

Cleanliness rating emerges as the most robust and economically important trust signal. A one-standard-deviation increase in cleanliness is associated with a 3.64% price premium ($p < .001$), holding

constant all property characteristics, location attributes, and city-specific effects. Given that cleanliness exhibits a standard deviation of 0.95 points on the 10-point scale, this estimate implies that moving from the 50th to the 84th percentile of the cleanliness distribution (approximately from 10 to a perfect 10 with consistent ratings) yields a price increase of nearly 4%. For a listing priced at the sample median of €210 for the standardized stay, this corresponds to approximately €7.65 for the same booking unit.

The prominence of cleanliness as a pricing determinant has important theoretical implications. Unlike generalized satisfaction, which aggregates multiple dimensions of service quality, cleanliness represents a specific, verifiable, and experience-based attribute that directly affects guest welfare. The significant monetization of cleanliness suggests that guests use granular quality signals to differentiate among listings in ways that broad satisfaction scores cannot capture. This finding aligns with signaling theory, which predicts that more precise and less manipulable signals should carry greater informational value in markets characterized by adverse selection.

Superhost status retains a positive and statistically significant effect (2.3%, $p < .05$) even after controlling for explicit quality metrics. This persistent premium suggests that the Superhost badge conveys information beyond observable ratings, potentially capturing dimensions such as communication quality, reliability, professionalism, and service consistency that are not fully reflected in cleanliness or satisfaction scores. The attenuation of the Superhost coefficient from 4.7% in Model 1 to 2.3% in Model 2 indicates that approximately half of the initial Superhost premium operates through its correlation with higher cleanliness and satisfaction, while the remainder represents independent signalling value.

In contrast, overall guest satisfaction does not exert a statistically significant effect in the pooled specification ($\beta = 0.008$, n.s.). This null finding is initially surprising given the theoretical importance of reputation in peer-to-peer markets. However, it becomes interpretable when considering measurement issues and construct validity. Guest satisfaction aggregates multiple evaluative dimensions including accuracy of listing description, host communication, check-in ease, location convenience, and value for money. Once specific quality dimensions (cleanliness), location attributes (distance to center), and property characteristics (capacity, bedrooms) are directly controlled, the residual variation in overall satisfaction may primarily reflect idiosyncratic preferences and non-price factors rather than monetizable quality differences.

The divergent effects of cleanliness and overall satisfaction provide empirical support for the hypothesis that platform-mediated markets reward specific, actionable quality signals over diffuse reputational measures. This granularity in trust monetization suggests platform design implications: reputation systems that decompose quality into distinct dimensions may facilitate more efficient matching and price discovery than those relying solely on aggregate ratings.

4.4. Heterogeneity in Trust Premiums Across Room Types

Model 3 introduces interaction terms between trust signals and room type to test whether the valuation of cleanliness and satisfaction varies across accommodation formats. The theoretical motivation for this heterogeneity is straightforward: different room types involve varying degrees of host-guest proximity, shared facilities, and privacy, which should systematically moderate the perceived importance of hygiene and service quality.

Figure 4 visualizes the marginal cleanliness premium by accommodation format, revealing pronounced segmentation. For entire homes and apartments, a one-standard-deviation increase in cleanliness is associated with a 2.69% price premium. This effect, while positive, is relatively modest compared to other room types, likely because guests renting entire units have exclusive control over the space and face lower hygiene risks from shared facilities or host proximity.

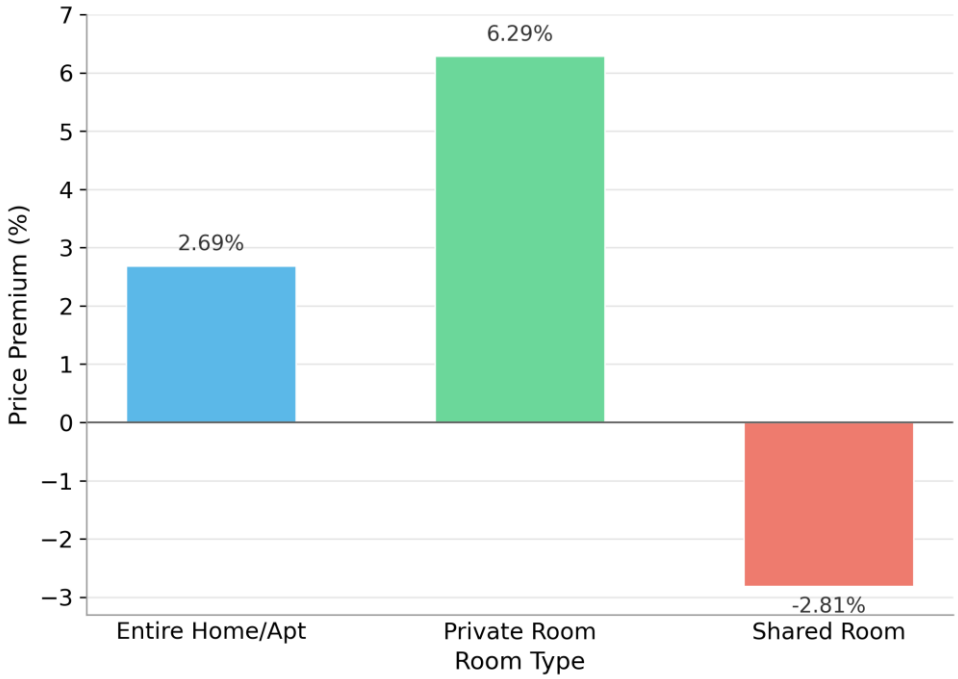


Figure 4. Cleanliness premium by room type

The cleanliness premium is most pronounced for private rooms, where it reaches 6.29% per standard deviation increase. This amplified effect is consistent with the elevated salience of cleanliness when guests share common areas with hosts or other occupants while maintaining private sleeping quarters. In such arrangements, guests cannot fully control their exposure to shared spaces, making host-demonstrated cleanliness standards particularly valuable. The premium in this segment is more than double that observed for entire homes, indicating substantial willingness to pay for verified hygiene in contexts of moderate privacy.

Shared rooms exhibit a negative and statistically fragile cleanliness coefficient of −2.81%. Because this coefficient is not statistically significant and rests on a small number of shared-room listings, it should be treated as inconclusive rather than as evidence of a negative premium, and the following behavioural interpretations are offered only as tentative hypotheses for future testing rather than as conclusions supported by the present data. Its direction may suggest that the shared room segment operates under a different pricing logic. Shared accommodations typically attract budget-conscious travellers for whom price sensitivity dominates quality considerations. In such markets, cleanliness ratings may fail to translate into premiums because demand is concentrated among price-minimizers who accept lower quality thresholds, or because ceiling effects in ratings provide insufficient differentiation in this segment.

Figure 5 presents marginal effects for guest satisfaction across room types. The pooled non-significance of satisfaction masks considerable heterogeneity. Shared rooms demonstrate the largest satisfaction premium at approximately 11.4%, suggesting that in lower-tier segments where specific quality signals like cleanliness may be less differentiated, broader measures of overall guest approval become more salient. This finding implies a potential substitution pattern wherein specific quality signals dominate in higher-quality segments (entire homes and private rooms), while generalized satisfaction becomes more informative in budget segments where quality variation operates along different dimensions.

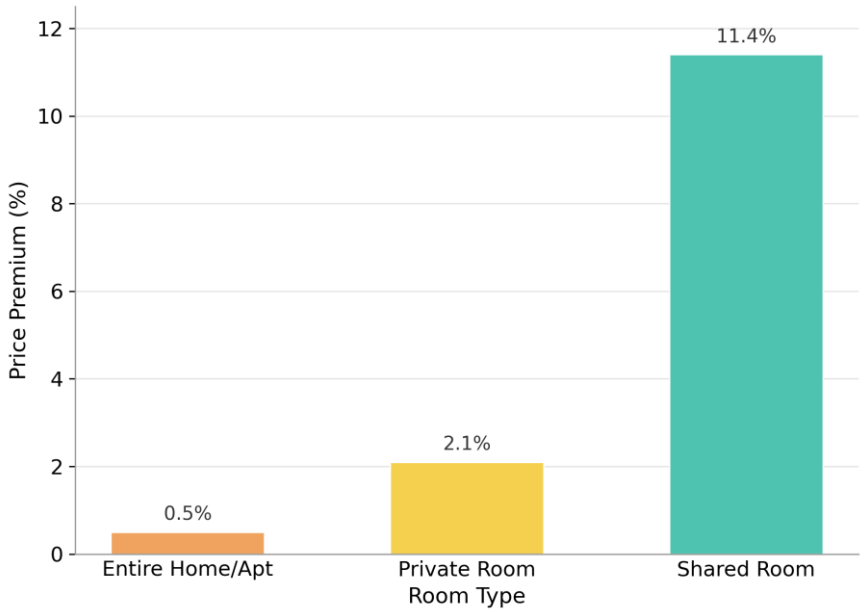


Figure 5. Guest satisfaction premium by room type

These interaction results collectively indicate that trust is not a homogeneous commodity uniformly valued across market segments. Rather, the monetization of specific trust dimensions depends critically on the structural characteristics of the accommodation format and the associated risk profiles perceived by guests.

4.5. Geographic Variation in Trust Monetization

Figure 6 displays city-specific cleanliness trust premiums estimated from separate regressions for each urban market. The magnitude of cleanliness monetization varies substantially across cities, ranging from less than 1.5% in Lisbon and Amsterdam to over 5% in Athens and approaching 4-5% in Vienna and Paris.

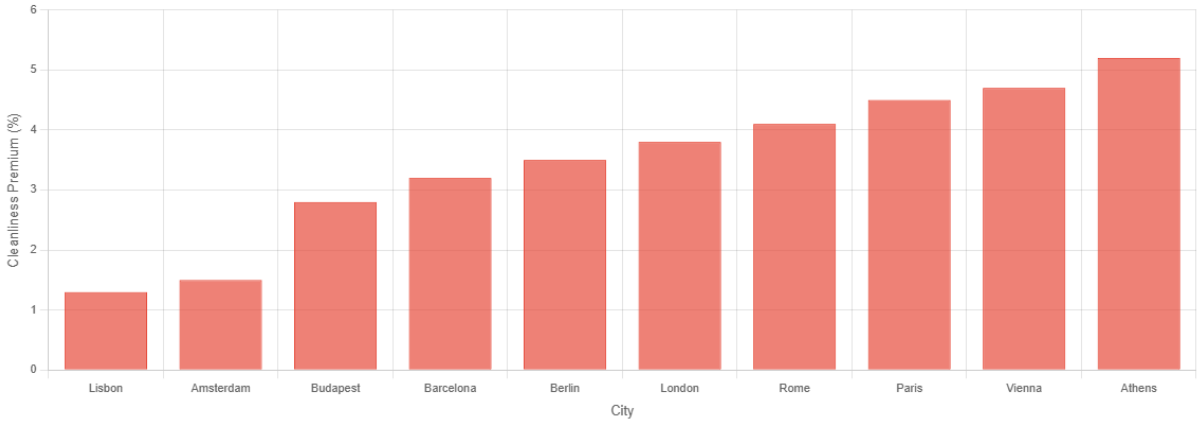


Figure 6. City-specific cleanliness trust premiums

This heterogeneity reveals that the economic value of platform trust signals is contextually determined by local market conditions. Athens exhibits the largest cleanliness premium at approximately 5.2%, potentially reflecting either greater baseline uncertainty about quality standards in a market with less mature short-term rental regulation, or stronger competitive pressure where cleanliness serves as a key differentiation mechanism in a price-sensitive market. Vienna and Paris, both high-tourism cities

with well-developed hospitality sectors, demonstrate cleanliness premiums in the 4-5% range, suggesting that even in sophisticated markets, hygiene signals remain economically consequential.

Conversely, Amsterdam and Lisbon show the smallest cleanliness premiums (1.5% and 1.3% respectively). In Amsterdam's case, this may reflect supply constraints and high baseline prices that leave limited scope for quality-based price discrimination, with location and availability dominating pricing decisions. Lisbon's lower trust premium might indicate either more homogeneous quality standards or market characteristics where other attributes overshadow cleanliness in determining competitive position.

The cross-city variation also suggests potential differences in guest composition and preferences. Markets dominated by luxury or business travelers may prioritize location and amenities over marginal differences in cleanliness ratings, whereas leisure-oriented or budget-sensitive markets may place greater weight on verified quality signals to mitigate uncertainty. Additionally, regulatory stringency may moderate trust premiums: cities with stricter licensing requirements and quality enforcement may exhibit lower trust premiums because baseline quality floors reduce the informational value of platform ratings.

These findings underscore that while platform trust mechanisms operate across markets, their economic significance is mediated by local market structure, competitive dynamics, regulatory environments, and demand composition. It should be emphasized, however, that the specific mechanisms invoked above to explain the cross-city differences regulatory maturity, supply constraints, competitive pressure, and demand composition are not directly measured or tested in this study. The city-level regressions establish that the cleanliness premium varies across markets, but they cannot adjudicate among these competing explanations. The interpretations are therefore presented as plausible, literature-consistent hypotheses that motivate future work rather than as findings the present design can confirm. A one-size-fits-all understanding of trust monetization is insufficient; context-specific analysis is necessary to understand when and where reputation systems are associated with substantial economic value.

4.6. Machine Learning Validation and Feature Importance

To assess the robustness of trust signal effects and evaluate their relative importance within a comprehensive pricing system, a Random Forest regression model was estimated using the full feature set including geographic coordinates. The model achieves strong out-of-sample predictive performance with an R^2 of 0.821 and a mean absolute error of 0.178 log price units (approximately €35 in level terms at median prices). This performance substantially exceeds the baseline hedonic model's R^2 of 0.649, indicating that non-linear relationships, high-order interactions, and fine-grained spatial effects captured by machine learning contribute meaningfully to price prediction.

Figure 7 displays the top 20 predictors of log price ranked by feature importance (mean decrease in Gini impurity). As expected, geographic coordinates (latitude and longitude) dominate the ranking, reflecting the fundamental importance of micro-location in urban accommodation pricing. Room type and distance to city center also rank highly, confirming the primacy of structural and locational factors documented in the hedonic regressions.

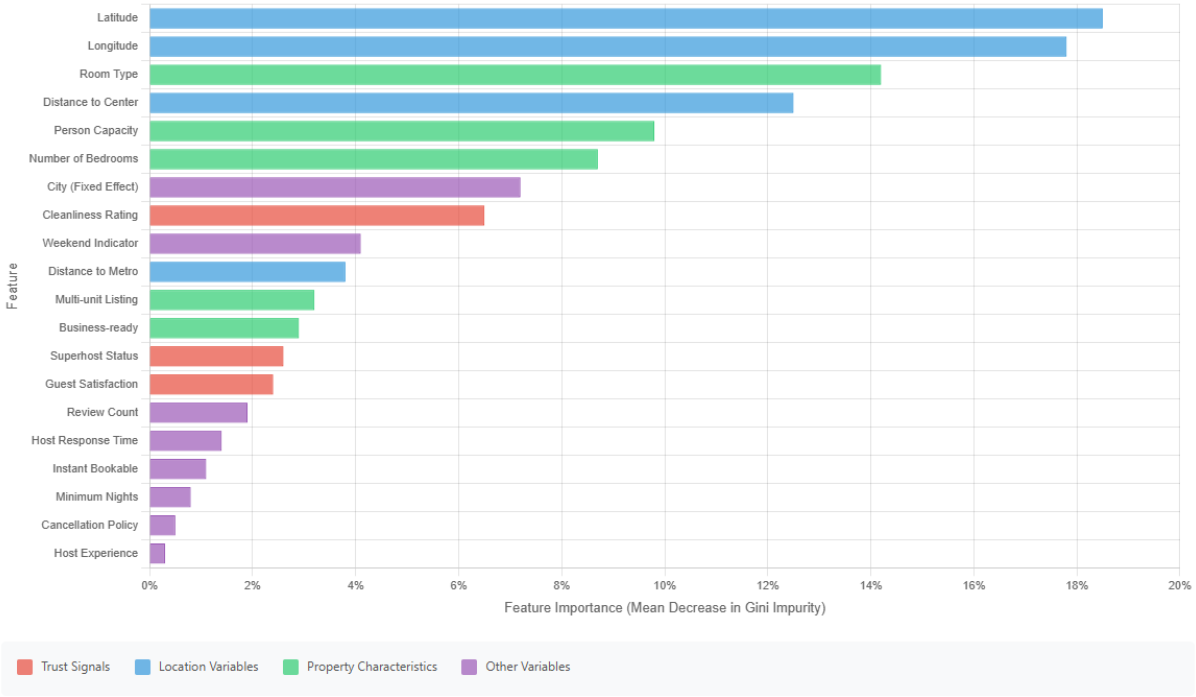


Figure 7. Feature importance rankings from Random Forest model

Critically, however, cleanliness rating and guest satisfaction both appear within the top 20 features and rank above several operational listing attributes such as multi-unit status and business-ready designation. Cleanliness rating ranks 8th in importance, positioned between bedroom count and weekend indicator, while guest satisfaction ranks 14th. This ordering confirms that trust signals contribute meaningfully to price formation even in flexible, non-parametric modelling environments that make no assumptions about functional form or interaction structure.

The convergence of findings across linear hedonic models and Random Forest analysis strengthens confidence that the trust premium is not an artefact of specification choice. Both approaches consistently identify cleanliness as an economically significant pricing determinant, suggesting that the relationship is robust to alternative modelling strategies.

The feature importance ranking also contextualizes the role of trust within the broader pricing hierarchy. While trust signals are not the dominant price driver's location, room type, and capacity remain paramount they constitute a meaningful secondary tier of determinants. This positioning aligns with theoretical expectations: in equilibrium, accommodation prices should primarily reflect scarce and non-replicable attributes (location, structural characteristics), with reputation signals operating as quality differentiators conditional on these fundamental constraints.

The machine learning results thus serve two functions: they validate the robustness of trust effects documented in parametric models, and they establish the relative magnitude of trust's contribution to overall price variation compared to traditional hedonic determinants. Trust matters, but it matters within a hierarchy where location and structural attributes remain foundational.

5. DISCUSSION

This study shows that platform-generated trust signals are systematically associated with economically meaningful price differences in peer-to-peer accommodation markets, with cleanliness ratings emerging as particularly powerful pricing correlates. The finding that a one-standard-deviation improvement in cleanliness is associated with an average 3.64% price premium represents a

substantial economic association, translating to approximately €7.65 per night for a median-priced listing or €229 over a month-long rental period. This association holds after accounting for property characteristics, spatial location, and city-specific market conditions, indicating that reputation signals are related to price beyond their correlation with these observable attributes. Because the design is cross-sectional, however, this should be read as a robust conditional association rather than as evidence that reputation systems causally create value; the possibility that unobserved listing quality jointly drives both higher cleanliness ratings and higher prices cannot be excluded and is addressed among the limitations.

The differential effectiveness of specific versus aggregate trust signals carries important theoretical implications. Cleanliness ratings consistently demonstrate significant pricing power across models and specifications, while overall guest satisfaction exhibits weak and inconsistent effects. This divergence suggests that granular quality signals may provide more actionable information to prospective guests than composite satisfaction measures. Cleanliness represents a directly observable, immediately consequential, and clearly defined attribute that guests can evaluate with relatively low cognitive effort. In contrast, overall satisfaction aggregates multiple dimensions including location accuracy, communication quality, and value perception, creating a diffuse signal that may be less diagnostic once specific attributes are directly controlled. This pattern is consistent with signalling theory, which predicts that precise, verifiable signals should carry greater informational value in markets characterized by information asymmetry. It should be noted, however, that this study does not directly measure signal precision or informational efficiency. The inference that cleanliness is a “more precise” signal is drawn indirectly from the relative magnitude and statistical significance of the coefficients, not from a direct test of how reliably each signal predicts realized service quality. This interpretation is therefore advanced as a theoretically motivated reading of the results rather than as a directly demonstrated property of the signals, and a formal assessment of signal precision is left to future research.

The pronounced heterogeneity in trust premiums across room types reveals that the economic value of quality signals depends critically on structural accommodation characteristics and perceived risk exposure (Nisar et al., 2020). Private rooms command cleanliness premiums more than double those observed for entire homes, consistent with the hypothesis that shared living arrangements amplify the salience of hygiene concerns (Nasreen & Ruming, 2020). When guests share common areas with hosts or other occupants while maintaining private sleeping quarters, they face elevated exposure to cleanliness standards beyond their direct control (Nasreen & Ruming, 2020). Under these conditions, verified cleanliness ratings become particularly valuable as risk-mitigation mechanisms. Conversely, guests renting entire homes exercise full control over their accommodation environment, reducing the urgency of ex-ante quality verification through platform ratings (Mccord et al., 2024). The negative and statistically fragile cleanliness coefficient for shared rooms suggests this segment may operate under fundamentally different pricing logic, where budget constraints dominate quality considerations and trust signals fail to translate into premiums (Hong & Yoo, 2020).

5.1. Theoretical Implications

The cross-city variation in trust monetization documented in this study challenges the assumption that platform reputation effects operate uniformly across markets. Cleanliness premiums range from approximately 1.3% in Lisbon to 5.2% in Athens, indicating that local market conditions substantially moderate the economic significance of trust signals. Several mechanisms may explain this heterogeneity. First, markets characterized by greater baseline uncertainty about quality standards may place higher value on credible verification mechanisms, explaining the elevated trust premiums in Athens relative to more mature markets. Second, regulatory environments influence both the composition of listings and the competitive dynamics among hosts, potentially affecting the degree to

which quality differentiation drives pricing. Third, demand composition matters. Markets dominated by budget-conscious leisure travellers may exhibit different trust premium structures than those serving business travellers or luxury segments. Fourth, supply constraints in high-price cities like Amsterdam may limit the scope for quality-based price discrimination, with availability and location dominating pricing decisions regardless of reputation metrics.

The machine learning analysis provides methodological validation of trust signal importance while contextualizing their role within the broader pricing hierarchy. The Random Forest model achieves substantially higher out-of-sample predictive performance than linear hedonic specifications, indicating that non-linear relationships and high-order interactions contribute meaningfully to price formation. Despite this flexibility, cleanliness and guest satisfaction consistently rank among the top predictors, positioned above numerous operational listing attributes. This convergence of findings across parametric and non-parametric approaches strengthens confidence that trust effects are not artefacts of functional form assumptions but represent genuine economic relationships. However, the feature importance rankings also confirm that location and structural characteristics remain the dominant price drivers. Geographic coordinates, room type, and distance to city center collectively explain substantially more variance than trust signals, consistent with urban economic theory emphasizing spatial fundamentals and scarce locational attributes (Chattopadhyay & Mitra, 2020; Gyódi & Nawaro, 2021).

5.2. Practical Implications

These findings carry practical implications for multiple stakeholder groups. For hosts, the results suggest that investments in observable cleanliness standards generate measurable returns in the form of higher sustainable prices, particularly in private room segments where hygiene salience is elevated. Cleanliness improvements appear more economically consequential than efforts to boost generalized satisfaction scores, indicating that hosts should prioritize tangible quality enhancements over diffuse service improvements. For platform operators, the differential effectiveness of specific versus aggregate ratings supports the value of granular reputation architectures that decompose quality into distinct dimensions. Platforms that provide detailed cleanliness metrics may facilitate more efficient matching and price discovery than those relying solely on composite ratings. For guests, the significant pricing of cleanliness ratings suggests that these signals provide credible quality information that reduces search costs and mitigates transaction risks.

From a regulatory perspective, the documented trust premiums indicate that reputation systems perform genuine economic functions beyond merely displacing traditional quality certifications. However, the cross-city heterogeneity in trust monetization suggests that one-size-fits-all regulatory approaches may be suboptimal. Markets where trust signals command large premiums may benefit from policies ensuring rating integrity and preventing manipulation, while markets where location and availability dominate pricing may require greater focus on spatial planning and housing supply interventions.

6. CONCLUSION

This study demonstrates that platform-generated trust signals constitute measurable economic assets in peer-to-peer accommodation markets, with cleanliness ratings operating as particularly powerful pricing mechanisms. Drawing on 51,448 Airbnb listings across ten European cities, the analysis reveals that specific quality dimensions generate larger and more consistent price premiums than aggregate satisfaction measures, suggesting that granular reputation architectures facilitate more efficient market coordination than composite ratings.

The heterogeneity in trust monetization across accommodation formats and geographic markets indicates that reputation effects are contextually determined rather than uniformly applicable. Private rooms command substantially larger cleanliness premiums than entire homes, reflecting differential risk perceptions associated with shared living arrangements. Cross-city variation in trust premiums ranges from minimal effects in supply-constrained markets to substantial monetization in environments characterized by greater baseline uncertainty, demonstrating that local competitive dynamics and regulatory environments moderate the economic significance of platform reputation systems.

The convergence of findings across hedonic regression and machine learning approaches provides robust evidence that trust signals contribute meaningfully to price formation even when accounting for comprehensive property characteristics, fine-grained spatial attributes, and flexible functional forms. However, the feature importance rankings confirm that location and structural characteristics remain primary price drivers, with trust signals occupying a secondary but significant tier of determinants.

These contributions advance understanding of how digital reputation systems are associated with economic value in platform markets. The findings demonstrate that trust is not a monolithic construct uniformly valued across contexts but rather a multidimensional phenomenon whose economic significance depends on signal granularity, accommodation structure, and market environment. By decomposing aggregate reputation into specific quality dimensions and examining systematic variation across room types and cities, this study provides a more nuanced account of trust monetization than prior research focused on overall ratings.

The fundamental insight emerging from this research is that in peer-to-peer markets where institutional quality certifications are absent, platform-constructed reputation systems perform genuine economic functions by reducing information asymmetry and enabling credible quality differentiation. However, the effectiveness of these systems depends critically on signal design, with specific observable attributes like cleanliness being associated with substantially greater pricing power than aggregate measures. As platform-mediated commerce continues expanding across sectors and geographies, understanding when, where, and how trust signals are associated with economic value becomes increasingly consequential for market efficiency, consumer welfare, and regulatory policy.

Limitations of the Study

Several limitations warrant acknowledgment. The cross-sectional design precludes causal inference about how exogenous changes in trust signals affect prices. While hedonic models control for observed confounders, unobserved host quality or marketing sophistication correlated with both ratings and pricing could bias trust coefficient estimates. The study examines European markets exclusively, limiting generalizability to regions with different institutional environments, tourism patterns, or cultural norms regarding hospitality. The analysis focuses on platform-provided trust metrics, excluding potentially important signals such as response time variability, cancellation histories, or textual review content that natural language processing might profitably exploit. Finally, the dataset captures a specific temporal snapshot and may not reflect how trust premiums evolve as markets mature, regulatory frameworks develop, or competitive intensity changes. Several additional limitations should be made explicit. Initially, the issues of reverse causality and omitted-variable bias require emphasis. It is possible that listings with higher prices or professional management simultaneously achieve better cleanliness scores and command higher prices due to unobserved quality. In this case, the estimated trust premiums would partly reflect this joint determination rather than a price response to the signal itself. The estimates should therefore be interpreted as conditional associations, and the causal language used in earlier drafts has been moderated throughout the manuscript. Additionally, the models omit several variables that are central to the Airbnb pricing and

reputation literature, most notably review volume (i.e. the number of ratings), host tenure, and host response rate. Review volume is particularly consequential because, in platform markets, reputation is generally understood to be the joint product of rating level and rating credibility. For example, a high cleanliness score based on a handful of reviews conveys different information than the same score supported by hundreds of reviews. As review quantity is not controlled for, the estimated trust premiums may be partially confounded with, or overstated relative to, a specification that also conditions on rating credibility. The treatment of spatial effects is also limited. While the hedonic models incorporate distance-to-centre measures and city fixed effects, and the Random Forest model includes latitude and longitude, these do not fully address spatial autocorrelation or neighbourhood-level heterogeneity, to which Airbnb prices are highly sensitive. Including coordinates in a machine-learning model does not substitute an explicit spatial-econometric treatment. Omitting neighbourhood fixed effects or localised clustering may affect the precision, and potentially the magnitude, of the coefficient estimates. Spatial hedonic approaches, such as those of Gyódi and Nawaro (2021), are a natural extension. The cleanliness and satisfaction measures exhibit pronounced ceiling effects and heaping at the maximum value. This compresses their variance and may mean that the assumption of a linear price response is only approximate. The reported premiums are therefore best understood as average associations over the largely upper-range observed distribution of ratings, rather than as constant marginal effects across the full theoretical scale.

Future Research

Future research should extend this analysis in several directions. Longitudinal designs tracking how individual listings' prices respond to rating changes would strengthen causal inference about trust effects. Cross-platform comparisons examining whether trust premiums differ between Airbnb, Vrbo, and emerging competitors could illuminate how platform-specific reputation architectures influence quality signalling effectiveness. Investigation of textual review content using natural language processing might reveal whether qualitative feedback provides information beyond numeric ratings. Analysis of trust premium evolution as markets mature could test whether reputation effects diminish as baseline quality improves or regulatory oversight intensifies. Finally, experimental interventions manipulating specific quality dimensions while holding others constant would provide definitive evidence about which trust signals matter most for price formation and guest decision-making.

Ethical Standards and Author Statement

Author Contributions (CRediT)

Gönül Akın: [conceptualization, literature review, writing – original draft]; Yavuz Selim Balcıoğlu: [methodology, data curation, formal analysis, software, visualization, writing – review & editing]

Ethics Committee Approval

There is no need for ethics committee approval for this study. The wet-signed consent form stating that an ethics committee decision is not required has been added to the article process file.

The authors are responsible for the accuracy of all sources used in this study and for their proper citation.

Author Contribution and Conflict of Interest

The authors declare that there is no financial, institutional, professional, or personal conflict of interest that could affect the planning, conduct, evaluation, or publication of this study, either between the authors or between the authors and any third parties or institutions.

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Data Availability Statement

The data used in this study are drawn from the publicly available multi-city European Airbnb dataset released by Gyódi and Nawaro (2021). No new data set was generated within the scope of this study.

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Statement on the Use of Generative Artificial Intelligence (GAI)

During the preparation of this work, the author used Deeply solely for language editing, improvement of academic expression, and linguistic clarity.

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