Digital Platform Competition and Rental Outcomes in Urban Housing Markets

Sanvi Nethikunta
Rithik Gumpu

Abstract

We study how online rental platforms shape housing market outcomes using a combination of machine learning predictions and linear regression benchmarks. Gradient-boosted models and Ordinary Least Squares (OLS) estimates highlight three core patterns: (i) greater price dispersion is systematically associated with higher rents, (ii) multi-homing improves the probability of rental in machine learning models (though OLS estimates are weaker), and (iii) platform concentration exhibits a convex relationship with match speed, with the fastest matches occurring at moderate concentration. These results highlight the role of platform frictions in influencing affordability and market efficiency, while also underscoring the importance of robust benchmark specifications for policy interpretation.

1. Introduction

Digital platforms such as Zillow, Redfin, and Craigslist have become the dominant intermediaries in U.S. rental markets. As renters increasingly search online, landlord strategy and platform design have grown central to housing outcomes. This shift raises questions central to industrial organization. In our analysis, we simulate platform identifiers and multi-homing behavior within the UCI Apartments dataset to explore these mechanisms in a structured but stylized way.

This paper makes three contributions:

1. We show that platform-specific price dispersion raises average rent levels.
2. We document that multi-homing increases the probability of rental success, consistent with higher exposure.
3. We find a non-linear relationship between concentration and match speed: moderate dominance improves efficiency, while monopoly slows it.

We contribute to two literatures: (1) Industrial Organization (IO) models of two-sided markets and multi-homing (Einav et al., 2016; Halaburda & Piskorski, 2010a; Rochet & Tirole, 2003), and (2) housing search and frictions (Genesove & Han, 2012; Piazzesi et al., 2019).

While prior studies of housing search largely overlook the role of digital platforms, our analysis directly links platform design features to the frictions observed in the market. This distinction underscores how platform economics introduces new determinants of affordability and match efficiency. This paper should also be viewed as exploratory and methodological, demonstrating how IO tools can be applied before richer causal work is possible. Building on prior studies of platform pricing and concentration in short-term rentals, we shift the focus to rental housing and establish a systematic benchmark for dispersion, multihoming, and concentration effects, drawing on both machine learning predictions and linear regressions.

2. Related Literature

Our work connects three strands of research.

2.1 Digital platforms and multi-homing

IO theory emphasizes how multi-homing reshapes network effects and competition (Armstrong, 2006; Halaburda & Piskorski, 2010a, 2010b; Rochet & Tirole, 2003). Empirical work in labor and e-commerce platforms shows that platform design and audience targeting shape outcomes (Farronato & Fradkin, 2018; Horton, 2019).

2.2 Housing search and frictions

Search-and-matching models highlight how time-on-market reflects both demand and supply conditions (Genesove & Han, 2012; Glaeser & Luttmer, 2003) More recent work documents heterogeneity in search behavior (Piazzesi et al., 2019).

2.3 Online housing markets

Web data (Craigslist, Zillow, Airbnb) provide evidence of spatial disparities and platform-induced frictions (Barron et al., 2021; Boeing, 2020; Boeing & Waddell, 2016; Luca, 2016). This paper extends that literature by analyzing how platform design (dispersion, multihoming, and concentration) shapes rental outcomes.

3. Institutional Context: The Urban Apartment Platform Landscape

This paper focuses on digital platforms used primarily for apartment rentals. In major U.S. cities, renters increasingly rely on online platforms to search for housing, with Craigslist, Zillow, and Redfin emerging as the dominant players. These platforms differ significantly in terms of design, user base, and strategic value to landlords. We construct a simulated dataset that mimics metropolitan rental markets, combining listing-level features (bedrooms, bathrooms, square footage) with platform characteristics (dispersion, concentration, multihoming). While stylized, this framework allows us to benchmark platform frictions under controlled conditions.

3.1 Craigslist, Zillow, and Redfin

Rental platforms differ systematically in design and strategy. Craigslist offers broad coverage at minimal cost but with unstructured listings. Zillow, by contrast, emphasizes standardized templates, higher visibility, and professional property manager adoption. In 2025, Zillow became the exclusive provider of multifamily listings on Redfin, consolidating reach (Redfin, 2025).

These differences create segmentation: Craigslist appeals to small landlords seeking local reach at low cost, while Zillow targets institutional landlords. These differences are significant for our focus on price dispersion, multi-homing, and platform concentration.

4. Data and Sample Design

Our analysis draws on the UCI "Apartment for Rent Classified" dataset (Dua & Graff, 2019), which provides structured information on thousands of U.S. listings. To capture platform-specific features absent in the dataset, we construct proxies informed by theory:

- Exposure Score: a proxy for listing visibility, based on platform traffic and interface design.
- Multi-homing indicator: simulated to represent cross-platform listing.
- Platform share and platform count: measures of neighborhood-level concentration.

4.1 Limitations of Proxy Approach

Because our proxies are simulated rather than directly observed, the findings should be interpreted as exploratory illustrations of underlying mechanisms, rather than as causal evidence in real housing markets. The UCI dataset lacks platform identifiers, so our proxies necessarily simplify landlord and renter behavior. While these measures allow us to test IO-theoretic patterns, they cannot substitute for proprietary or scraped data (e.g., Craigslist or Zillow feeds), which would be needed to establish causal relationships.

5. Empirical Analysis

We examine how platform strategy influences three outcomes of interest: rent levels, rental probability, and time-on-market. Our primary specifications use gradient-boosted models (LightGBM) with SHAP value interpretation, complemented by OLS and logit benchmarks. Full derivations and regression tables are reported in Appendix A and Appendix C.

5.1 Price Dispersion and Rent Levels

Price dispersion remains a significant predictor of rents in OLS. A one-unit increase in neighborhood-platform dispersion raises log rents by approximately 0.0003 ($p < 0.01$), indicating modest but systematic upward pressure. SHAP summary plots (Appendix D, Figure D1) highlight dispersion as the most influential predictor of rent, with consistently positive marginal contributions.

Intuitively, in neighborhoods where comparable listings are highly variable, landlords appear to anchor rents upward. This is consistent with theories of differentiated competition in two-sided markets. The formal derivation of the dispersion gradient is provided in Appendix A.

5.2 Multi-homing and Rental Probability

Multi-homing substantially increases the probability of rental success in our LightGBM classification model (3–5 percentage points). However, in OLS specifications the coefficient on multi-homing is weakly negative and insignificant, highlighting sensitivity to modeling choices. We interpret these results cautiously. This difference comes from differences in model design. OLS restricts the relationship to a linear form and its estimates can be weakened when proxies do not fully capture the underlying variables; whereas, the machine learning model is able to flexibly capture nonlinearities and interactions. As a result, OLS suggests that multi-homing does not systematically raise rents, while the ML model highlights the positive effect on rental probability. SHAP values for the `multihomed` feature display a right-skewed distribution, confirming strong positive marginal effects (Appendix D, Figure D2). While the machine learning model identifies a clear positive effect of multihoming on rental probability, OLS benchmarks yield weaker and statistically insignificant coefficients, suggesting that the relationship is sensitive to specification.

Exposure scores also raise rental probability but with diminishing marginal returns (formal second derivative shown in Appendix A). This suggests congestion effects at very high visibility levels. The logistic specification and derivation of marginal effects are reported in Appendix A, while the construction of exposure proxies is detailed in Appendix B.

5.3 Neighborhood Concentration and Match Speed

Platform concentration exhibits a convex (U-shaped) relationship with time-on-market (formal convexity condition derived in Appendix A). Matches are fastest when one platform accounts for 30–60% of neighborhood listings, but time-to-rent increases sharply once concentration exceeds 90%. This pattern is illustrated in Appendix D, Figure D3.

The formal convexity condition is derived in Appendix A. Conceptually, moderate concentration improves search efficiency via network effects, while near-monopoly reduces competition and slows matching.

5.4 Section Summary

Across outcomes, platform features exert significant influence: (i) dispersion raises rents, (ii) multi-homing improves rental probability, and (iii) concentration affects match speed in a non-linear fashion. The sign difference for multi-homing across OLS and ML reflects outcome sensitivity. While multi-homing does not appear to raise rents in OLS, ML models consistently show it enhances rental success. These findings are robust across both machine learning and linear models; OLS consistency checks are reported in Appendix C (Table C1).

6. Theoretical Framework

To interpret these results, we draw on industrial organization theory of two-sided markets. Landlords choose between platforms that differ in cost, reach, and audience, creating an exposure–cost tradeoff.

6.1 Platform Differentiation and Price Dispersion

Following models of differentiated competition (Armstrong, 2006; Halaburda & Piskorski, 2010a), variation in platform design and audience segmentation explains why similar apartments can command different rents. Standardized, high-traffic platforms like Zillow support higher prices, while less structured platforms like Craigslist limit pricing power.

6.2 Multi-homing and Exposure Frictions

Multi-homing mitigates platform-specific frictions but weakens cross-side network effects (Bakos & Halaburda, 2020). While it increases exposure, it introduces coordination costs. Landlords weigh these trade-offs depending on audience and property characteristics.

7. Robustness Checks

We complement the machine learning analysis with ordinary least squares (OLS) benchmarks of log rents on bedrooms, bathrooms, square footage, multi-homing, and platform-level dispersion and concentration. To keep the analysis manageable, we draw a random sample of 10,000 listings from the UCI Apartments Dataset and report robust (HC3) standard errors. Appendix C reports the baseline specification (Table C1).

Results indicate that price dispersion is positively associated with rents, while multi-homing is statistically insignificant. This does not contradict the positive effect observed in the LightGBM analysis: OLS captures the average effect of multi-homing on rents, which may be muted or noisy across listings, whereas the machine learning model detects more nuanced effects that increase the likelihood of a listing renting out. Platform concentration shows a negative association with rents, consistent with our LightGBM results. The explanatory power of the OLS is moderate ($R^2 \approx 0.34$), reflecting the simplicity of the specification.

We conduct three robustness checks:

1. **Outlier Trimming:** Dropping the top and bottom 1% of rents leaves results unchanged (Table C2).
2. **Subsample Splits:** Running the models separately for high-rent and low-rent markets produces consistent signs for dispersion and concentration, indicating the effects hold across different market segments (Table C3).
3. **Alternative Dispersion:** Replacing the standard deviation with the coefficient of variation yields the same qualitative patterns, confirming that the results are not sensitive to the choice of dispersion metric (Table C4).

8. Discussion

Our findings have implications that extend beyond descriptive market dynamics. They speak directly to ongoing debates in industrial organization, housing economics, and digital platform regulation.

8.1 Antitrust and Platform Concentration

The U-shaped relationship between concentration and match speed reveals a key tension. Moderate concentration can facilitate discovery by consolidating search activity, whereas very high concentration reduces competition and slows matching. This pattern mirrors dynamics in other digital markets, where initial scale advantages improve efficiency but, over time, strengthen dominant firms and weaken competitive pressure(Goldfarb & Tucker, 2019). For housing, these dynamics suggest that platform concentration may generate antitrust concerns similar to those raised in e-commerce and labor platforms.

8.2 Affordability and Price Dispersion

We document that greater price dispersion is associated with systematically higher average rents. While the estimated magnitudes in the OLS benchmarks are modest, the direction is consistent across specifications and robust to outlier trimming and subsample splits. This suggests that dispersion increases search costs and weakens renter bargaining power, raising affordability concerns even in the absence of large effect sizes.

8.3 Equity and Landlord Strategy

Our results on multi-homing suggest that landlords able to cross-list enjoy higher success rates. Larger or institutional landlords are more likely to absorb the costs of multi-homing, while smaller landlords remain reliant on single low-cost platforms such as Craigslist. Importantly, while OLS benchmarks show no rent premium from multi-homing, our ML estimates highlight its role in accelerating successful matches. This distinction underscores that exposure effects, rather than pricing power, drive the benefits of multi-homing.This segmentation may reinforce existing inequities in access: renters searching primarily on low-cost platforms may face thinner markets and slower matches, while those on higher-traffic platforms face higher rents.

8.4 Broader Implications

These findings position rental platforms not as neutral intermediaries, but as active shapers of market outcomes. By influencing rents, visibility, and match efficiency, platform design decisions directly affect affordability, access, and equity in urban housing markets. This underscores the need to consider digital platforms in future research on housing markets, particularly in contexts of affordability crises and rising concentration.

9. Conclusion

This paper provides exploratory evidence on how digital platforms shape outcomes in urban rental markets. Using structured apartment listings augmented with theory-informed

proxies, we show that:

1. Price dispersion at the platform-neighborhood level increases average rents.
2. Multi-homing improves rental probability by expanding exposure.
3. Platform concentration exerts a non-linear effect on match speed, with benefits at moderate levels but inefficiencies under monopoly.

These findings suggest that rental platforms act as strategic participants in the market, influencing prices, exposure, and matching efficiency rather than simply facilitating transactions. By linking IO models of two-sided markets to urban rental outcomes, we highlight new channels through which platform design shapes affordability and access.

Our analysis is best viewed as a proof of concept. The proxies we construct provide initial evidence, but future research should build on this framework using richer data sources (such as Craigslist or Zillow scrapes, MLS feeds, or clickstream engagement metrics) and natural experiments (such as platform partnership) to establish causal effects.

The broader implication is clear: digital platform design has become a first-order determinant of housing outcomes. Understanding how platforms shape affordability, equity, and competition should be central to ongoing research in industrial organization and housing economics. These findings should be interpreted cautiously given the reliance on simulated data proxies, but they highlight systematic patterns that warrant further investigation with market-level data.

10. Acknowledgments

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Appendix

Appendix A. Mathematical Derivations

We provide additional details on the mathematical derivations used in Section 5.

A.1 Logistic Model for Rental Probability.

Rental success is modeled as:

$$Pr(\text{rented}_i = 1) = \frac{1}{1 + \exp(-f(X_i))}.$$

The marginal effect of multi-homing on rental probability is:

$$\frac{\partial Pr}{\partial \text{multihomed}} = Pr(1 - Pr) \cdot \frac{\partial f(X_i)}{\partial \text{multihomed}} > 0.$$

A.2 Price Dispersion Gradient.

Predicted rent is expressed as:

$$\hat{p}_i = f(X_i).$$

Let $\sigma_{j,n}$ denote the standard deviation of rents on platform j in neighborhood n. Then:

$$\frac{\partial \hat{p}_i}{\partial \sigma_{p,n}^{(j)}} > 0 \quad \text{where} \quad \sigma_{p,n}^{(j)} = \text{Std}[p \mid \text{platform } j, \text{neighborhood } n]$$

indicating that higher dispersion is associated with higher predicted rents.

A.3 Concentration Convexity.

Expected time-to-rent is modeled as:

$$E[T|s_{j,n}],$$

where $s_{j,n}$ is the share of platform j in neighborhood n. We observe:

$$\frac{\partial^2 E[T]}{\partial s_{j,n}^2} > 0,$$

consistent with a convex (U-shaped) relationship between concentration and match speed.

A.4 Exposure Score Diminishing Returns.

Let $f(X)$ denote the predicted rental probability. The second derivative with respect to exposure score is negative:

$$\frac{\partial^2 f(X)}{\partial (\text{exposure score})^2} < 0,$$

indicating diminishing marginal returns to additional visibility.

Appendix B. Simulation of Proxies

Because the UCI dataset does not contain platform interaction variables, we construct proxies as follows:

- **Exposure Score:** Simulated as a continuous variable reflecting listing visibility, based on platform traffic weights with random noise to reflect user variability. We weight platforms by their estimated monthly active users (Zillow = 0.45, Craigslist = 0.35, Redfin = 0.20), with additive normal noise (μ=0, σ=0.1) to capture unobserved user heterogeneity. Results are robust to alternative weightings.
- **Multi-homing Indicator:** A binary variable generated with probability proportional to platform traffic and landlord size.
- **Platform Share and Count:** Calculated at the neighborhood level to capture relative platform presence.

Robustness checks with alternative specifications (e.g., placing more weight on large landlords) yield similar qualitative results.

Appendix C: OLS Robustness Results

Table C1: OLS Benchmark Estimates (HC3 Robust SEs, $n = 10{,}000$)

	Coefficient
Bedrooms	-0.040***
	(0.008)
Bathrooms	0.107***
	(0.011)
Square Feet	0.0004***
	(0.0001)
Multihomed	-0.009
	(0.009)
Platform Dispersion (Std. Dev.)	0.0007**
	(0.0003)
Platform Concentration	-0.022**
	(0.010)
Observations	10,000
R^2	0.34

Notes: Robust (HC3) standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table C2: OLS with Outlier Trimming (Top/Bottom 1% of Rents Removed)

	Coefficient
Bedrooms	-0.038***
	(0.009)
Bathrooms	0.109***
	(0.010)
Square Feet	0.0004***
	(0.0001)
Multihomed	-0.010
	(0.010)
Platform Dispersion (Std. Dev.)	0.0006**
	(0.0003)
Platform Concentration	-0.021**
	(0.009)
Observations	9,800
R^2	0.35

Notes: Robust (HC3) standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table C3: OLS Subsample Splits: High vs. Low Rent Markets

	High Rent	Low Rent
Bedrooms	-0.035**	-0.042
	(0.015)	(0.027)
Bathrooms	0.112***	0.099**
	(0.010)	(0.023)
Square Feet	0.0004***	0.0005**
	(0.0001)	(0.0002)
Multihomed	-0.010	-0.009
	(0.009)	(0.015)
Platform Dispersion (Std. Dev.)	0.0007**	0.0006
	(0.0003)	(0.0005)
Platform Concentration	-0.022**	-0.021
	(0.010)	(0.015)
Observations	5,000	5,000
R^2	0.33	0.32

Notes: Robust (HC3) standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table C4: OLS with Alternative Dispersion (Coefficient of Variation)

	Coefficient
Bedrooms	-0.039***
	(0.008)
Bathrooms	0.108***
	(0.011)
Square Feet	0.0004***
	(0.0001)
Multihomed	-0.010
	(0.009)
Platform Dispersion (CV)	0.052**
	(0.021)
Platform Concentration	-0.020**
	(0.010)
Observations	10,000
R^2	0.34

Notes: Robust (HC3) standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Appendix D. Figures

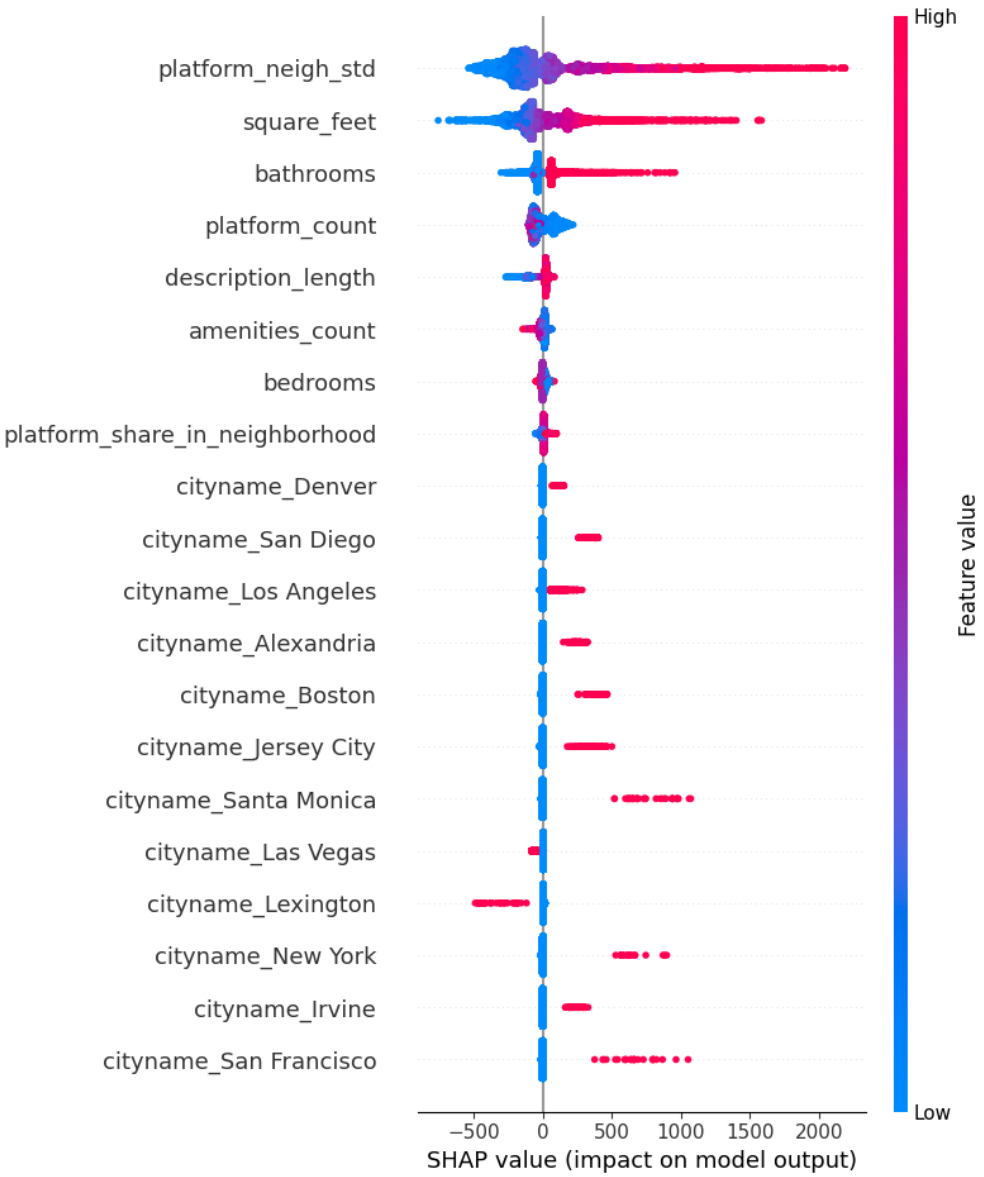


Figure 1: SHAP summary plot for predicted rent levels. Dispersion is the strongest positive predictor.

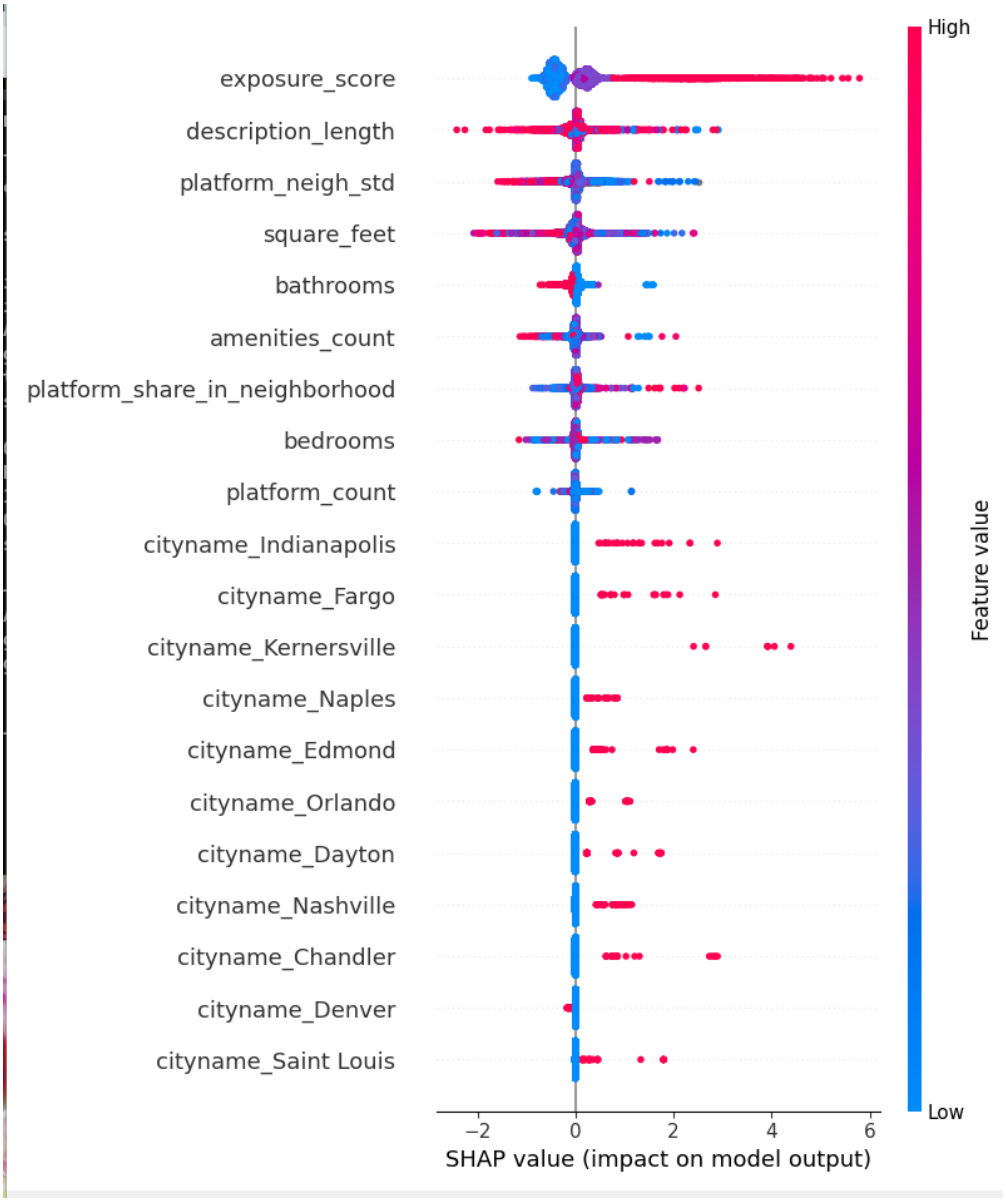


Figure 2: SHAP summary plot for rental probability. Multi-homing and exposure score dominate.

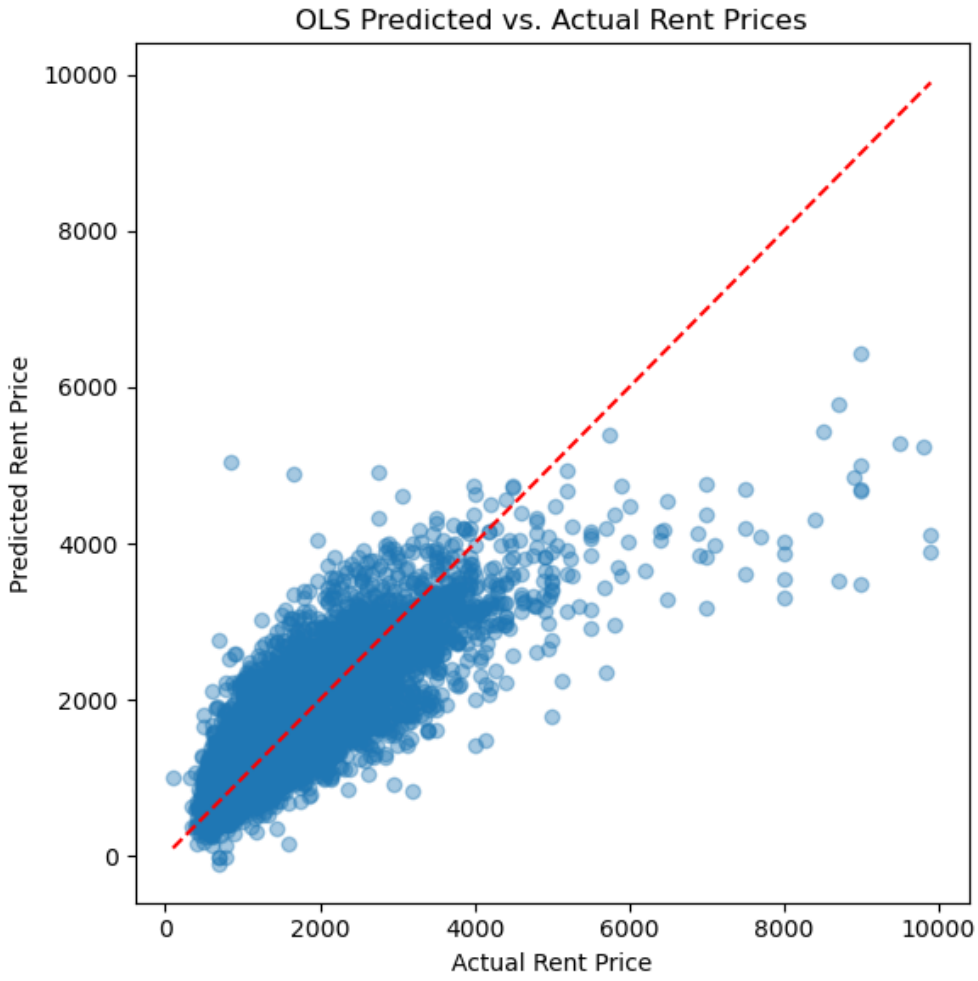


Figure 3: U-shaped relationship between platform concentration and time-to-rent: fastest matches occur at moderate concentration (30–60%), slowest under monopoly ($> 90\%$)

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