Seeing the Future: How AI-Generated Future-State Visuals Shape Matching in Two-Sided Markets

Yushan Zhou[1], Renyu Zhang[2]

[1] The Chinese University of Hong Kong, Hong Kong, China, yushanzhou@cuhk.edu.hk

[2] The Chinese University of Hong Kong, Hong Kong, China, philipzhang@cuhk.edu.hk

Two-sided market platforms are increasingly deploying generative AI tools that transform latent future states into salient decision-relevant information. We study this phenomenon in the context of AI-generated future-state visuals on a large Chinese resale housing platform. Exploiting the platform's staggered roll-out of AI Visual across major cities, we examine how this information-design intervention affects matching efficiency, transaction prices, and post-transaction satisfaction. We find that AI Visual significantly improves matching efficiency, reducing days on market by approximately 10% for buyers and 20% for sellers, and increases transaction prices by about 2.7%, consistent with improved seller-side and platform-side outcomes. The effects are more pronounced for poorly renovated properties, listings handled by low-performing agents, and properties in thicker markets. Mechanism analyses suggest that these effects are not explained by observable seller price-adjustment behavior. Instead, they are consistent with demand-side responses in which AI-generated visuals reduce information gaps about post-renovation potential, lower search effort, and facilitate faster convergence in buyers' valuation processes. However, these efficiency gains come with a trade-off in matching quality: seller satisfaction increases, whereas buyer post-transaction satisfaction declines, consistent with expectation disconfirmation from stylized future-state representations. We further show that high-performing agents' expertise can mitigate this buyer-side backfire while preserving efficiency gains. Our findings highlight generative AI as a powerful information-design tool in two-sided markets: it can reduce demand-side frictions and improve short-run platform outcomes, but platforms must manage expectation formation through targeted deployment and complementary human expertise.

Key words: AI Visual, Two-sided Market, Information Design, Matching Efficiency, Matching Quality, Digital Platform

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1. Introduction

Generative AI tools such as AI agents and copilots are increasingly reshaping business practices across a wide range of fields (Ide and Talamàs 2025, Brynjolfsson et al. 2025, Chica et al. 2024). Beyond automating existing operational tasks, generative AI can also serve as a new information design lever. That is, it changes what information is presented to market participants, how uncertainty is represented, and how users form beliefs before making decisions. This role is particularly important in two-sided markets, where matching outcomes depend critically on how participants interpret incomplete information about potential counterparties, products, or future states. Real estate platforms constitute a typical form of two-sided markets and have become increasingly central to housing transactions (Jiang et al. 2024). Importantly, operations outcomes in real estate markets not only affect platform performance but also have broader implications for social equity, as pricing dynamics and investment patterns directly shape the distribution of economic opportunities across communities (Bekkerman et al. 2024). Recently, platforms such as Zillow have introduced a new class of AI design tools, AI-generated post-renovation visuals that illustrate how a property may appear after renovation, into online property listings to help buyers better visualize potential living spaces.[1]

By leveraging both generative AI capabilities and rich platform data, these visuals provide informative representations of properties' potential future states. When combined with immersive technologies (VR), AI-generated future-state visuals can reduce buyers' cognitive effort in mental simulation of renovation outcomes and lower perceived mismatch risk, thereby influencing search behavior and purchase decisions.[2] While such AI tools are increasingly adopted in practice, little is known about the business implications of such tools in two-sided markets, particularly with respect to key matching outcomes such as matching efficiency, matching quality, and transaction prices.

When searching for properties and making purchase decisions, buyers often face substantial cognitive burdens in envisioning a property's appearance after renovation (Davis 2026).[3] Evaluating such properties requires buyers to form beliefs about their post-renovation state, a process that is cognitively demanding and subject to substantial uncertainty.[4] This uncertainty can increase search intensity, prolong the matching process, and complicate negotiation. AI-generated future-state visuals directly address this challenge by reducing the information gap regarding a property's latent post-renovation value. In this sense, AI Visual functions as an information design intervention: rather than changing the underlying property attributes, it changes the informational environment in which buyers evaluate the property's future potential. By providing a concrete and standardized representation of the property's potential condition, these visuals externalize what would otherwise be a cognitively demanding inference process. As a result, they lower buyers' uncertainty and improve the precision of their valuation. By reducing both cognitive and informational frictions, buyers can evaluate properties more efficiently, leading to fewer on-site visits, shorter search durations, and ultimately faster transactions. More generally, AI-generated future-state visuals reshape

[1] See "Zillow's new AI staging feature is impressively unimpressive," *The Verge*, Sep 2025, https://www.theverge.com/news/775465/zillow-ai-virtual-staging; and "Real Estate Is Entering Its AI Slop Era," *Wired*, Oct 2025, https://www.wired.com/story/real-estate-is-entering-its-ai-slop-era/.

[2] For brevity, we also refer to AI-generated future-state visuals as AI Visuals throughout the remainder of the paper.

[3] Buyers often decide to renovate properties either for personal use or for resale.

[4] Since this "future state" is not directly observable at the time of decision-making.

how buyers form beliefs about future outcomes by providing a salient reference point for evaluating renovation potential.

Beyond streamlining the search process, AI-generated future-state visuals can also influence negotiation dynamics between buyers and sellers. The information gap reduction has two important implications. First, improved valuation precision allows buyers to converge more quickly on acceptable options, reducing search intensity and accelerating matching. Second, by lowering perceived mismatch risk and uncertainty about renovation outcomes, these visuals increase buyers' willingness to pay. As buyers become more confident in their valuation, they engage in less intensive bargaining and are less likely to continue searching for alternatives (Harding et al. 2003, Han 2008). Taken together, these forces suggest that AI-generated future-state visuals not only enhance matching efficiency but also contribute to higher transaction prices. We therefore conceptualize this primary mechanism as an information frictions alleviation channel, whereby AI-generated future-state visuals reduce information gaps in buyers' belief about a property's future state.

Through the information frictions alleviation channel, the impact of AI-generated visuals on matching efficiency is likely to vary systematically across properties, market environments, and real estate agents. First, AI-generated visuals are expected to be particularly valuable for properties with lower baseline attractiveness (e.g., those that are undecorated or only minimally decorated). In these cases, the relevant decision object, namely the post-renovation state of the property, differs substantially from its current observable condition, requiring buyers to rely heavily on mental simulation and inference. As a result, information gaps and evaluation uncertainty are especially pronounced. AI-generated future-state visuals help mitigate this challenge by making latent future quality more observable and reducing the cognitive burden associated with forming beliefs about post-renovation outcomes. Consequently, heterogeneity along the renovation dimension provides a particularly direct and diagnostic test of the information frictions alleviation channel, as it captures settings where the gap between current and future states is the largest.

On the intermediary side, lower-performing agents may benefit disproportionately from AI-generated visuals. These agents often face limitations in effectively framing a property's latent potential, which can exacerbate information gaps between buyers and properties. AI-generated future-state visuals serve as a standardized and scalable communication tool that facilitates the transmission of information about future outcomes, thereby reducing reliance on individual agent capability. As a result, the incremental impact of AI Visual is expected to be larger for lower-performing agents and smaller for high-performing agents.

In a thicker market, buyers face a larger set of alternatives, which increases the complexity of comparison and amplifies cognitive and informational frictions in the evaluation process (Li and Netessine 2020). At the same time, agents operating in such environments face higher transaction intensity and capacity constraints, which may further limit their ability to bridge information gaps. AI-generated visuals can help alleviate these information frictions by reducing the cognitive cost of evaluating each property. Therefore, we predict that the effects of AI Visual are more pronounced for properties in thicker neighborhood markets.

In addition to improving matching efficiency, AI-generated future-state visuals may also introduce unintended consequences on matching quality. Specifically, these visuals may present stylized or overly optimistic representations of a property's potential state. If buyers rely heavily on such representations during decision-making, they may form inflated expectations about the post-transaction experience. Based on expectation disconfirmation theory, when the actual outcome falls short of the visually presented potential, buyers may experience a decline in post-transaction satisfaction (Guan et al. 2023). Therefore, AI-generated visuals may distort buyer expectation formation, thereby giving rise to a potential efficiency–quality trade-off in two-sided markets.

The lack of clear theoretical predictions on how AI-enabled information design affects two-sided matching motivates us to ask three key research questions. First, how do AI-generated future-state visuals affect key matching outcomes, including matching efficiency (measured by days on market for buyers and sellers) and transaction prices and how do these effects vary across characteristics of properties, buyers, and agents? Second, what are the underlying behavioral mechanisms through which these effects operate on the demand side and the supply side of the market? Third, how do AI-generated future-state visuals affect matching quality (i.e., post-transaction satisfaction of buyers and sellers), and if negative effects on quality indeed arise, what strategies could mitigate such backfire effects. Overall, this study aims to provide novel insights into how AI-generated future-state visuals shape two-sided matching processes and market dynamics.

To systematically study the real-world effects of AI-generated visuals as an information design lever in two-sided markets, we partnered with one of the largest resale housing platforms in China. Exploiting the staggered roll-out of AI-generated future-state visuals across major Chinese cities, we find that access to AI Visual significantly improves matching efficiency. This improvement is reflected in a substantial reduction in days on market for both buyers and sellers. Specifically, the deployment of AI-generated visuals reduces days on market by approximately 10 percent for buyers and by about 20 percent for sellers. In addition, access to AI Visual leads to higher transaction prices, with an average increase of approximately 2.7 percent in unit prices, consistent with improved seller-side and platform-side outcomes.[5]

In further investigation of the mechanisms underlying the main effects, we find that seller-side price adjustment behavior does not account for the observed results. Instead, demand-side responses

[5] This is because the platform charges a fixed percentage commission based on transaction prices, so higher transaction prices directly increase platform revenue.

play a central role. In particular, AI-generated future-state visuals are associated with reduced search effort and faster convergence in decision-making, consistent with reduced uncertainty in buyers' valuation process. Consistent with the above prediction, we also provide empirical evidence that properties with poorer renovation quality, those handled by low-performing agents, and properties located in thicker markets experience larger gains in both matching efficiency and transaction prices. These heterogeneity patterns are broadly consistent with the information frictions alleviation channel. [6]

Finally, we find that the deployment of AI Visual does not necessarily improve matching quality. While AI Visual leads sellers to report higher post-transaction satisfaction, buyers' post-transaction satisfaction declines. This pattern is consistent with expectation disconfirmation, whereby stylized future-state representations lead buyers to form overly optimistic expectations about realized outcomes. We provide empirical evidence consistent with the over-optimistic representation channel. We further show that transactions handled by high-performing agents exhibit a muted buyer-side backfire effect, suggesting that agent expertise can mitigate the decline in buyer satisfaction without sacrificing efficiency gains.

Overall, our study provides systematic evidence that AI-generated future-state visuals operate as a powerful information design lever in two-sided markets. By transforming an otherwise latent and difficult-to-evaluate future state into salient visual information, AI Visual reduces demand-side information frictions, improves matching efficiency, and enhances platform-level outcomes. At the same time, we document a potential trade-off between matching efficiency and matching quality: while AI Visual improves efficiency and seller outcomes, it can reduce buyers' post-transaction satisfaction due to expectation disconfirmation. That is, these gains can come with a buyer-side satisfaction backfire, suggesting a tension between short-run conversion and post-transaction quality. These findings reveal that the benefits of generative AI are not universal and depend critically on how AI-mediated information shapes and influences decision-making on both sides of the market throughout the matching process. In addition, our results underscore the importance of a cautious and targeted deployment of AI-generated visuals, particularly in market segments characterized by severe informational frictions, where such tools can be complemented with human expertise. Leveraging the experience and domain knowledge of high-performing agents can mitigate the potential backfire effect of AI on buyer satisfaction while preserving efficiency gains, thereby enabling platforms to balance short-term improvements in matching efficiency with long-term matching quality.

The remainder of this paper is organized as follows: §2 summarizes the related literature; §3 introduces the background of our study and the platform we collaborated with; §4 presents the

[6] The heterogeneity analysis by renovation condition provides the most direct test of the information friction alleviation channel

dataset, summary statistics, and identification strategy; §5 provides the empirical results on matching efficiency, along with related heterogeneity analyses and underlying mechanisms; §6 presents the effects on matching quality and provides prescriptions; §7 reports the robustness checks; and §8 concludes the paper.

2. Literature Review

Our paper contributes to three main streams of related literature that provide diverse insights into AI in operations and service operations. First, our paper contributes to recent literature that investigate the applications of AI algorithms in the broad OM domains, highlighting their potential to enhance operational efficiency. For instance, in the procurement field, Cui et al. (2022) document how AI algorithms can support procurement decision-making. In the context of driver performance, prior studies show that AI chatbots and AI-based feedback can support drivers' decision-making processes and thereby enhancing driving performance (Xu et al. 2024, Cui et al. 2025, Hao and Xu 2025). More generally, recent studies investigate how AI algorithms improve worker productivity by optimizing personalized recommendations for service workers (Snyder et al. 2025), after-sales services (Ni et al. 2024), item-picking (Kim et al. 2024, Knight et al. 2024) and packing processes (Sun et al. 2022, Bai et al. 2022). Beyond the effects of AI assistants on operational efficiency in various OM domains, our study investigates a novel application of GenAI that generates future-state visuals and assesses its impact on matching quality and efficiency in a two-sided market. Conceptually, our study shifts attention from AI as an automation or recommendation technology to AI as an information design tool that shapes users' belief formation and matching decisions under uncertainty.

More specifically, our paper contributes to the growing literature on platform operations that investigate how AI technologies enhance platform efficiency and service quality (Brynjolfsson et al. 2025, Zhang and Narayandas 2025, Wiles et al. 2025, Yang et al. 2025, Wang et al. 2025, Knight et al. 2026, Kim et al. 2024). One line of the literature investigates how the adoption of GenAI assistants influences digital platforms' operational efficiency and service quality. For instance, Zhang and Narayandas (2025) find that AI assistants improve customer service efficiency and emotional engagement, enabling faster responses and deeper interactions. Brynjolfsson et al. (2025) show that the introduction of a generative AI assistant improves worker productivity by 15% and increases customer satisfaction while reducing complaints. Wiles et al. (2025) find that algorithmic writing assistants increased a job seeker's hiring rate by 8% and wage by 10%, showing that the digital platform can benefit from the optimization of labor services brought about by the deployment of AI writing assistants. The other line of this literature focuses on how AI-generated metadata or investment recommendations influence platform efficiency and matching quality. For example, Zhang et al. (2024) find that AI-generated metadata can significantly enhance user-content matching and content consumption for UGC platforms. Yang et al. (2025), leveraging a field experiment in an investment advisory setting, show that human-AI co-created investment advice was adopted more frequently than purely AI-generated one. Our paper contributes to this strand of literature by emphasizing how digital platforms deploy GenAI-powered vision tools to optimize operational efficiency and service quality.

Second, this paper builds on the growing body of research examining how the application of AI algorithms on real estate platforms can enhance market outcomes (Fu et al. 2025, 2022, Yan et al. 2025, Raymond 2023, Tanlamai et al. 2024, Aramayo et al. 2023, Zou and Khern-am nuai 2023). Existing studies mainly focus on pricing algorithms and VR tools, while little is known about how AI-generated post-renovation visuals shape transaction outcomes, particularly for matching efficiency and quality. For example, Fu et al. (2025) show that automated valuation algorithms (i.e., Zestimate) improve both seller profit and buyer surplus by enhancing the matching quality. Yan et al. (2025) find that VR adoption increases information richness in property transactions, thereby accelerating sales and raising prices. Raymond (2023) documents that digitization leads to increased participation of algorithmic investors without crowding out human investors. Instead, human investors shift towards properties where algorithmic valuation is less precise. We extend this line of research by examining how, beyond common algorithmic features such as intelligent pricing and virtual reality tools, AI-generated post-renovation visuals enhance both matching efficiency and service quality on real estate platforms.

Third, our paper contributes to emerging research on the business impact of AI-powered image-generation tools (Hui et al. 2024, Demirci et al. 2025, Nu et al. 2024, Lysyakov and Viswanathan 2023). This stream of research mainly focuses on how the adoption of AI-powered image-generation tools affects gig platform workers' productivity and labor supply. For example, Hui et al. (2024) show that freelancers in image-intensive occupations experience negative impacts on employment and earnings following the adoption of image-generating LLMs. Demirci et al. (2025) find that image-generating AI technologies reduce job postings related to image creation by 17%, directly affecting freelancing platforms. Another line of literature examines how offline stores deploy AI-powered image-generation tools to optimize their operations (Zheng et al. 2025, Nu et al. 2024). In the context of sustainability, Nu et al. (2024) demonstrate that integrating AI-based visual recognition into restaurant food waste feedback systems reduces food waste by as much as 30%. Zheng et al. (2025) provide empirical evidence that video-based AI misconduct monitoring unintentionally reduces restaurants' operational performance. Thus far, much of the attention has centered on AI-powered image-generation tools that assist freelancers in creative work and AI algorithms embedded in cameras to classify and detect issues such as food waste or employee misconduct. Our empirical context is unique in the sense that AI-generated visuals designed to present future state can affect matching efficiency and quality by reducing buyers' cognitive decision-making costs and mitigating information asymmetry.

3. Setting

We collaborate with one of the largest secondary housing transaction platforms in China (hereafter "Platform V"). The firm operates resale housing brokerage services across more than 100 Chinese cities. In 2020 alone, Platform V facilitated over two million transactions with a total value exceeding RMB 2 trillion (approximately USD 280 billion). Platform V's business model centers on maintaining a proprietary listing database, facilitating matching and transactions between buyers and sellers, and charging a commission as a percentage of the completed transaction value. Homeowners who intend to sell their properties list them on the platform, and employed agents assist sellers in uploading property information and setting listing prices according to sellers' preferences. To enhance the visual presentation of listings, the platform deploys professional photographers and specialized equipment to create panoramic images and virtual reality (VR) tours, enabling buyers to conduct immersive VR property viewings through the app.

During our sample period, the typical buyer's search and matching process unfolds as follows. First, buyers initiate their search on the app by filtering properties based on criteria such as location and layout.[7] Second, buyers freely browse shortlisted properties and check them in detail using the VR feature before contacting the agent responsible for a particular listing. Third, agents communicate with buyers online to better understand their preferences and provide additional property information. Based on this interaction, agents typically recommend an additional 4–10 properties beyond the buyer's initial selection to facilitate buyers' comparison and decision-making. Fourth, buyers conduct VR viewings of these alternative properties and narrow down their choices to approximately 2–4 properties for on-site visits. Fifth, buyers arrange in-person viewings and, if interested, engage in on-site negotiations. Finally, buyers may continue searching online to compare alternative options with potentially higher value-for-money (or better preference alignment) via VR tour, or proceed to contract signing and transaction completion.

A central managerial challenge faced by Platform V is how to leverage digital technologies to enhance buyer engagement and the property evaluation process, thereby increasing conversion rates and shortening transaction cycles.[8] Building upon its existing VR-based tools, Platform V

[7] During the sample period, more than 80% of buyers in the sample cities initiated their search through the online app, while fewer than 20% visited offline brokerage stores directly.

[8] During the 2020–2021 sample period, China's housing market remained in a boom phase, and the platform's business continued expanding.

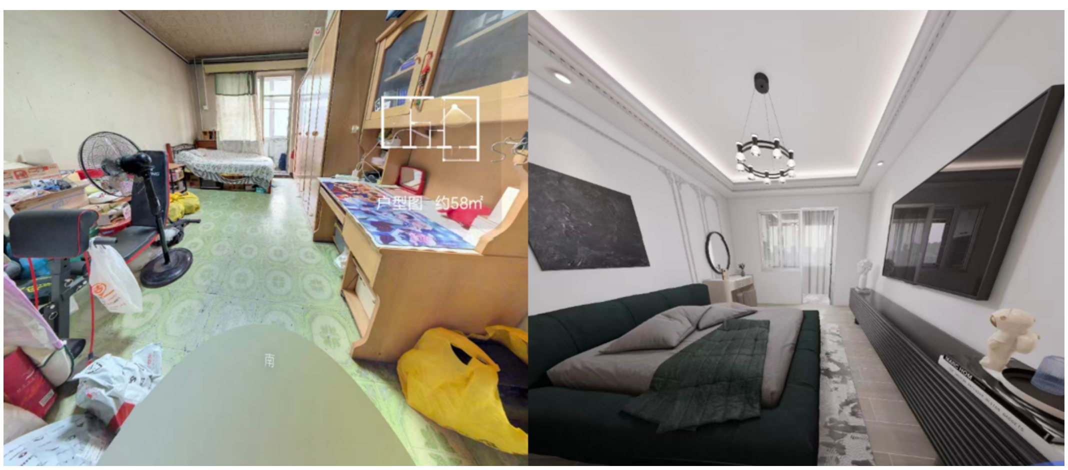
began developing an AI-generated post-renovation visualization feature in late 2019. This feature generates immersive VR tours that depict how a property could appear after renovation and integrates these visualizations directly into the online listing interface. The system operates by applying generative AI models to the original property images and layout information to produce stylized representations of potential post-renovation states. Importantly, these AI-generated visuals are presented alongside the original property images and VR tours, rather than replacing them. As a result, buyers can simultaneously observe both the current condition of the property and its simulated future state. Figure 1 illustrates an example of this feature's interface.

Given that Platform V operates in more than 100 cities, the firm initially introduced the AI Visual feature as a pilot program in a subset of cities. The objective was to evaluate its effectiveness before deciding on broader implementation and to determine whether deployment should be standardized or left to sellers' discretion. Specifically, in 12 major sample cities, the platform introduced the feature in four staggered waves over approximately ten months, spanning from autumn 2020 to summer 2021. Notably, the activation of AI-generated visuals was mandatory for all listings following roll-out during the period of experiment, allowing us to isolate the causal impact of the technology without concerns of selective adoption.

Figure 1 Example of the AI Visual Interface

(a) Original VR Viewing Interface

(b) AI Visual Interface



(c) Comparison Interface: Actual Property and AI Visual

Note: This figure illustrates the original VR viewing interface, the interface enhanced with AI Visual support, and a side-by-side comparison between the actual property condition and the AI-generated post-renovation visualization. Notably, after the introduction of AI Visual, buyers can still freely use the original VR function to view the property in its actual condition, and they can compare the two displays within the same interface.

4. Research Design

4.1. Data and Summary Statistics

Our data come from a unique proprietary dataset provided by our partner, Platform V. The sample covers 12 cities in which the AI Visual feature was introduced in a staggered manner. The observation window spans from June 1, 2020 to December 31, 2021, fully covering the four roll-out waves.[9] Appendix Table EC.1 reports the anonymized city IDs and the specific dates on which the AI Visual feature was introduced in each batch. The dataset consists of four components: (1) transaction-level data on resale housing, (2) supply-side panel data capturing sellers' dynamic pricing adjustments, (3) demand-side data on buyers' on-site property viewings, and (4) post-transaction ratings and structured review tags submitted by buyers and sellers. Together, these four components comprehensively capture matching outcomes and the matching process in this two-sided housing market.

First, the transaction-level dataset contains detailed information on each resale housing transaction, including transaction date, neighborhood location, sellers' days-on-market (measured as the duration from listing to sale), buyers' days-on-market (measured as the duration from the start of search to transaction completion), transaction price, and the property's last listed price. It also includes a rich set of property characteristics, such as floor area, floor level, number of rooms, and building age. In addition, we can observe buyer demographics (i.e., gender and age group) as well as characteristics of the agent handling the transaction, including gender and performance level. The richness of the transaction-level data enables us to measure key matching outcomes, such as matching efficiency and transaction performance, and provides a foundation for exploring underlying mechanisms.

Second, there is a weekly panel dataset capturing sellers' dynamic pricing adjustments on the supply side. This weekly panel dataset tracks dynamic pricing adjustments made by sellers for each listed property. Specifically, it records both the frequency and magnitude of weekly price revisions. The magnitude is defined as the percentage change relative to the previous listing price (i.e., the price adjustment divided by the prior total listing price and multiplied by 100), where positive values indicate upward price revisions and negative values indicate downward revisions. The dataset also includes key property characteristics, such as floor area and floor level. This information allows us to examine how sellers respond to the introduction of AI Visual and, more broadly, to explore the supply-side mechanisms operating in this two-sided market.

Third, we assemble a demand-side weekly panel dataset on buyers' on-site property viewings. This dataset records the number of on-site visits for each listed property in each week, along with

[9] Within our sample, the AI Visual feature was introduced in October 2020, January 2021, May 2021, and August 2021.

associated property characteristics. On-site viewing represents a critical stage in buyers' search and decision-making processes, as it enables them to physically experience the property after online browsing. Therefore, this dataset helps us understand how AI Visual influences buyers' search efforts.

Fourth, we utilize post-transaction review data submitted by buyers and sellers on the platform's rating system. This dataset includes an overall rating on a discrete 1–5 scale, where higher values indicate greater satisfaction. In addition, reviewers may select structured textual tags to indicate agreement with specific evaluation statements, such as "accurate property recommendation," "good appearance," and "clear explanation of property features." This post-transaction evaluation dataset enables us to measure buyers' and sellers' perceptions of matching quality. Finally, Table 1 reports summary statistics for the main variables used in our analysis, and Appendix Table EC.2 provides detailed variable definitions.

Table 1 Summary Statistics

	Mean	SD	p10	p90
Log(Buyer_days)	2.708	1.646	0	4.913
Log(Seller_days)	4.049	1.192	2.485	5.525
Log(Price)	10.266	0.754	9.348	11.270
Log(Last listed Price)	10.297	0.760	9.374	11.310
Sold<3months	0.517	0.500	0	1
Viewing	1.599	2.816	0	4
Adjust_times	0.181	0.540	0	1
Adjust_mag	-0.421	2.244	-1.820	0
Rating(buyer)	4.783	0.503	4	5
Rating(seller)	4.757	0.572	4	5
Recommend_optimal	0.248	0.432	0	1
Appearance	0.342	0.474	0	1
Intro_well	0.227	0.419	0	1
Poor_Renovated	0.444	0.497	0	1
Mkt_thic	2.329	2.266	0.440	4.900
Performance	3.428	1.359	1.130	4.710
Agent_gender	0.683	0.465	0	1
Buyer_gender	0.526	0.499	0	1
Buyer_age	3.313	1.516	1	5
Building Size	84.306	34.197	48.500	128
Building Age	0.238	0.426	0	1
Renovation	2.476	0.641	2	3
Floor	2.119	0.799	1	3
Subway	0.532	0.499	0	1
Rooms	2.186	0.795	1	3

Note: This table reports summary statistics for the main variables used in the analysis. p10 and p90 denote the 10th and 90th percentiles, respectively.

4.2. Identification Strategy

To isolate the causal effect of AI Visual on matching outcomes, we employ a staggered DiD design. Platform V rolled out the AI Visual feature across our sample cities in four sequential waves. [10] According to the platform's internal roll-out documentation, the timing and ordering of roll-out across sample cities were random, in the sense that they were not determined by local market conditions, sales performance, or demand-side characteristics. Although the company states that the roll-out across cities was randomized, we further conduct regression analyses to examine whether local housing market conditions can predict adoption timing. Appendix Table EC.20 shows that these aggregate local housing conditions do not predict the timing of adoption, providing additional support for the randomized roll-out order. Hence, this institutional feature provides an ideal setting to distinguish treated groups—those occurring after the deployment of AI Visual—from control groups in cities where the feature had not yet been introduced during the same period. Notably, once introduced in a given city, the AI-generated visual feature was automatically activated for all listings on the platform. That is, activation was mandatory rather than optional during our sample period, ensuring that all treated listings were uniformly exposed to the AI-generated visuals. This feature also mitigates concerns about endogenous adoption or selective usage by sellers.

Following Brynjolfsson et al. (2025), the model specification for our staggered DiD approach is as follows:

$$Y_{inct} = \delta_t + \alpha_n + \beta PostTreat_{ct} + \gamma X_i + \epsilon_i \tag{1}$$

The dependent variable, Y_{inct}, captures transaction-level matching outcomes for property i located in neighborhood n, city c, and transacted in time t. To comprehensively measure matching efficiency and transaction performance, we consider three primary outcome variables: sellers' days-on-market, buyers' days-on-market, and housing transaction prices.[11]

The independent variable of interest, $PostTreat_{ct}$, is an indicator equal to one for transactions occurring after the introduction of the AI Visual feature in city c, and zero otherwise.[12] We include year–month fixed effects, δ_t, to account for common time-varying shocks, such as seasonal housing market cycles and aggregate price fluctuations. We also include neighborhood fixed effects, α_n, to capture time-invariant location-specific heterogeneity. Because neighborhoods are nested within

[10] Specifically, Platform V rolled out the AI Visual feature across our 12 sample cities in four sequential waves in October 2020, January 2021, May 2021, and August 2021.

[11] In the robustness analysis, we also use an indicator for whether a listing is sold within three months as an alternative proxy for matching efficiency, as reported in Section 7.6

[12] Because the AI feature was introduced at the platform-city level, all transactions occurring in a treated city after the roll-out are considered exposed to the AI Visual feature.

cities, the inclusion of neighborhood fixed effects absorbs all time-invariant city-level heterogeneity. We control for a set of property characteristics, X_i, including floor area, number of rooms, and floor level. Standard errors are clustered at the district level.[13] Because the AI feature was introduced at the platform-city level, treatment varies at the city-by-time level. Our identifying variation comes from the staggered roll-out across cities, comparing changes in outcomes after adoption in treated cities with contemporaneous changes in not-yet-treated cities. The granular transaction-level data allow us to measure outcomes precisely, include rich property controls and neighborhood fixed effects, and examine heterogeneity across properties, agents, and buyers; however, inference must still account for the city-level roll-out structure. We therefore report robustness checks using city-level and city-by-week clustered standard errors.[14]

Recent econometric studies have shown that conventional two-way fixed effects estimators in staggered DiD settings may yield biased estimates when treatment effects vary across adoption cohorts or over time (Brynjolfsson et al. 2025, Borusyak et al. 2024, Callaway and Sant'Anna 2021). To address this concern, we also re-estimate our main specifications using the alternative estimators developed by Callaway and Sant'Anna (2021), Borusyak et al. (2024) in the robustness analysis and find that our results remain unchanged. Finally, we assess the validity of the identifying assumption by examining pre-treatment trends in the outcome variables. Event-study estimates show no evidence of differential pre-trends between treated and control groups prior to the roll-out, further supporting the credibility of our research design. Finally, one potential concern is that our transaction-level results may be affected by duration selection or censoring in the full listing sample. To address this concern, Column (1) of Appendix Table EC.18 uses the full sample of listed properties and defines the dependent variable as an indicator for whether a property is sold within three months after listing. The results remain robust, suggesting that our main findings are unlikely to be driven by selective sale timing or censoring among listed properties.

5. Results

In this section, we turn to analyze the overall empirical results. We begin by examining the effects of deploying AI Visual on matching efficiency and transaction prices. We then conduct extensive heterogeneity analyses and explore the underlying mechanisms through which these effects operate, considering both the supply and demand sides of the market.

[13] We also adopt more conservative inference by clustering standard errors at the city level, as well as implementing two-way clustering at the district-time and city-time levels. The results remain robust under these alternative specifications.

[14] Notably, our identification strategy is further supported by recent work with a closely related empirical setting. For example, Heeyon et al. (2026) examine a city-level Airbnb policy shock that differentially affected Los Angeles and San Diego, and identify its effects using granular listing-level observations from the treated city, Los Angeles, and the control city, San Diego.

5.1. Effects on Matching Efficiency and Transaction Prices

Table 2 examines the causal effect of the deployment of AI Visual on the primary matching outcomes, namely, days on market for buyers, days on market for sellers, and transaction prices, by estimating Equation (1). In Column (1), controlling for location and time fixed effects, the estimated coefficient on $PostTreat$ is negative and statistically significant, indicating that the deployment of AI Visual reduces buyers' days on market by about 10%. In Column (2), we further include control variables related to property characteristics, and the results remain consistent.[15] Columns (3) and (4) present the effects of AI Visual on days on market for sellers, with Column (4) incorporating additional controls. The estimated coefficients on $PostTreat$ are negative and statistically significant across both specifications. Taking Column (4) as an example, we find that the deployment of AI Visual reduces days on market for sellers by about 20% relative to the pre-treatment mean. Finally, Columns (5) and (6) report the effects of AI Visual on unit transaction prices. We find that AI Visual has a positive and statistically significant impact on transaction prices, corresponding to a $\exp(0.0273) - 1 = 2.77\%$ increase relative to the average pre-treatment price.

Overall, these results document that the deployment of AI Visual significantly improves matching efficiency in the two-sided market and also generates positive effects on transaction prices. Consistent with our prediction, the preliminary evidence suggests that AI-generated future-state visuals indeed substantially reshape matching outcomes and primarily benefit sellers and the platform.[16]

Appendix Figure EC.1 further presents the accompanying event-study estimates for the impact of AI Visual on matching efficiency and transaction prices. In Appendix Figure EC.1a and EC.1b, we observe no significant pre-treatment differences between the treatment and control groups prior to the introduction of AI Visual, supporting the parallel trends assumption. Following the deployment, there is an immediate and persistent decline in days on market for both buyers and sellers. Similarly, the parallel trends assumption holds for transaction prices, as shown in Appendix Figure EC.1c.

5.2. Preliminary Mechanism Analyses from Supply Side and Demand Side

In this subsection, we aim to provide preliminary evidence on the behavioral channels through which AI-generated visuals may influence matching efficiency and transaction outcomes, from both the demand and supply sides. We emphasize that these analyses are not intended to offer direct identification of the underlying mechanisms. Rather, they document observable changes in market

[15] Regarding the effects on buyers' days on market, we note that our estimates capture the intention-to-treat (ITT) effect of AI Visual availability, rather than treatment-on-the-treated effects based on realized buyer usage. Due to data limitations, we do not observe detailed buyer-level engagement (e.g., buyer-level usage frequency or time spent). Meanwhile, platform statistics indicate that approximately 80% of buyers used the AI Visual feature during the sample period, suggesting that our ITT estimates likely reflect substantial exposure in practice.

[16] This is because higher transaction prices imply higher realized transaction prices, consistent with improved seller-side outcomes. Since the platform earns revenue by charging a percentage-based commission on transaction prices, it benefits not only from faster transaction cycles but also from increased commission revenues.

Table 2 Effects of AI Visual on Matching Efficiency and Transaction Prices

	Log(Buyer_days)		Log(Seller_days)		Log(Price)	
	(1)	(2)	(3)	(4)	(5)	(6)
PostTreat	-0.1044***	-0.1047***	-0.2157***	-0.2176***	0.0271***	0.0273***
	(0.020)	(0.019)	(0.029)	(0.030)	(0.006)	(0.006)
Building Size		0.0045***		0.0057***		-0.0009***
		(0.000)		(0.000)		(0.000)
Building Age		-0.0366*		0.0240***		-0.0041**
		(0.019)		(0.007)		(0.002)
Floor		-0.0021		0.0230***		-0.0082***
		(0.004)		(0.008)		(0.002)
Renovation		-0.0306***		-0.1232***		0.0493***
		(0.007)		(0.009)		(0.003)
Rooms		0.0476***		-0.0670***		0.0350***
		(0.009)		(0.013)		(0.007)
Subway		0.0124		-0.0073		0.0131**
		(0.011)		(0.007)		(0.005)
Constant	2.7384***	2.3368***	4.1123***	4.0306***	10.2585***	10.1461***
	(0.006)	(0.037)	(0.009)	(0.035)	(0.002)	(0.019)
Observations	193,926	193,924	193,926	193,924	193,926	193,924
Adjusted R^2	0.112	0.123	0.057	0.077	0.943	0.946
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors clustered at the district level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

participants' behaviors that are consistent with the proposed mechanisms and help shed light on how AI Visual may shape the matching process.[17]

5.2.1. Supply Side Mechanism On the supply side, AI Visual can potentially reshape the seller expectations and their pricing adjustment behaviors in the real-estate market.[18] In general, sellers rely on subjective assessments of their property's appeal and may misvalue their listings due to limited feedback on buyer preferences. The introduction of AI-generated post-renovation visuals provides sellers a more objective signal of how buyers perceive their property's potential. By visualizing the property's post-renovation visuals, sellers may recognize additional value that was not apparent from the current condition. This perception may prompt sellers to adjust their expectations upward, anticipating that buyers will be willing to pay higher prices for properties that appear more desirable after renovation. AI-generated visuals increase seller expectations, leading to upward price anchoring and higher transaction prices.

[17] Given data limitations, these measures should be interpreted as suggestive rather than definitive evidence of belief updating or valuation precision

[18] Here, we use sellers' pricing adjustment behavior as a proxy for seller-side responses. While we acknowledge that this measure does not capture all dimensions of seller behavior, it represents a primary and observable margin of adjustment within the scope of our data.

To examine whether sellers respond to the deployment of AI Visual through adjustments in their pricing behavior, and thereby help explain the main effects, we construct a weekly panel dataset of sellers' pricing adjustments. We introduce two new variables: $Adjust\_times$, which measures the number of price adjustments made to a listing in a given week, and $Adjust\_mag$, which captures the average magnitude of price adjustments.[19] We then replace the dependent variable in Equation (1) with $Adjust\_times$ and $Adjust\_mag$, respectively, and re-estimate the regression. The results, reported in Appendix Table EC.3, show that the estimated coefficients on $PostTreat$ are statistically insignificant in both specifications. These findings suggest that sellers do not systematically adjust their pricing behavior in response to the deployment of AI Visual. Therefore, we find no evidence that observable seller-side price-adjustment behavior accounts for the main effects.

5.2.2. Demand Side Mechanism From the demand side, a primary mechanism through which AI Visual operates is by influencing buyers' search and decision-making processes. In the housing market, buyers frequently consider post-purchase renovation—either for personal occupancy or for future resale. Evaluating such properties therefore requires buyers to mentally simulate the property's potential "future state" after renovation. This process is cognitively demanding and inherently uncertain, particularly for properties that are in poor condition. These visualization-related information frictions can increase the number of property visits required, prolong search duration, and delay purchase decisions. Buyers may hesitate or defer commitment because they struggle to form a clear and confident assessment of the property's latent value. In our context, AI-generated visuals directly reduce such information frictions by providing a concrete and credible representation of the property's post-renovation appearance. By externalizing the mental simulation process, the technology lowers buyers' cognitive costs and uncertainty, and facilitates more efficient comparison across alternatives.

As a result, buyers can evaluate properties more quickly and with greater confidence, leading to fewer required viewings, shorter search durations, and ultimately faster transactions. In this way, AI Visual enhances matching efficiency primarily by streamlining buyers' information processing and decision-making. Hence, if the demand-side mechanism is indeed operative, the deployment of AI Visual should reduce the number of property viewings required by buyers, thereby decreasing further search and improving matching efficiency. To test this prediction, we construct a weekly panel dataset at the listing level from the demand side and replace the dependent variable with the number of property viewings in a given week. We then re-estimate our baseline specification. The results, reported in Column (1) of Table 3, show that AI Visual significantly reduces the number

[19] $Adjust\_mag$ is defined as the percentage change in the listing price relative to the pre-adjustment total price (multiplied by 100). Negative values indicate price reductions.

of house viewings required on the demand side, providing empirical evidence in support of the demand-side mechanism.

Second, if AI Visual reduces buyers' search efforts and narrows their consideration set, buyers may become less likely to identify lower-priced alternatives with identical characteristics. Under this rationale, we would expect AI Visual to increase the final listing price of transacted properties. To test this prediction, we replace the dependent variable with the logarithm of the last listed price of the transacted house, $Log(LastListedPrice)$. The estimation results reported in Column (2) of Table 3 indicate that AI Visual has a positive and statistically significant effect on the last listed price of the transacted property, further supporting the demand-side mechanism. Appendix Figure EC.2a and EC.2b presents the corresponding event-study estimates for these two analyses. The pre-treatment coefficients are statistically indistinguishable from zero, supporting the parallel trends assumption.

Finally, AI-generated future-state visuals can also shape negotiation dynamics between buyers and sellers. By reducing information frictions and improving buyers' valuation precision, these visuals help buyers form more confident beliefs about a property's potential value. As uncertainty declines, buyers are less likely to engage in intensive bargaining or attempt to extract additional surplus through negotiation. In this sense, AI Visual not only facilitates faster matching but also alters the bargaining stage of the transaction process by reducing negotiation effort.

To empirically examine this mechanism, we construct a measure of buyers' on-site negotiation effort based on the discount from the last listed price to the final transaction price. Specifically, we define the on-site negotiation ratio as:

$$\text{On-site Negotiation Ratio} = \frac{\text{Last Listed Price} - \text{Transaction Price}}{\text{Last Listed Price}} \times 100\%. \tag{2}$$

A higher value of this ratio indicates more intensive bargaining by buyers. We then replace the dependent variable in Equation (1) with this measure and re-estimate the model. The estimation results, reported in Appendix Table EC.4, show that the coefficient on $PostTreat$ is negative and statistically significant. This indicates that the introduction of AI Visual significantly reduces buyers' on-site negotiation intensity by 0.9%. The magnitude of the estimate suggests a meaningful decline in bargaining effort following the roll-out. Taken together, these findings provide additional support for the information frictions alleviation channel: by improving valuation certainty and reducing perceived mismatch risk, AI-generated visuals decrease buyers' incentives to negotiate aggressively, thereby contributing to higher transaction prices and more efficient matching outcomes.

Table 3 **Demand-side: Effects of AI Visual on Buyers' Search Efforts and Search Outcomes**

	(1) Viewing	(2) Log(Last listed Price)
PostTreat	-0.2188***	0.0191***
	(0.052)	(0.006)
Building Size	0.0016*	-0.0009***
	(0.001)	(0.000)
Building Age	0.0009	-0.0012
	(0.001)	(0.002)
Floor	0.0008	-0.0086***
	(0.001)	(0.002)
Renovation	-0.0031**	0.0492***
	(0.001)	(0.003)
Rooms	-0.0011	0.0364***
	(0.002)	(0.007)
Subway	0.0019	0.0130**
	(0.002)	(0.005)
Constant	1.7083***	10.1818***
	(0.026)	(0.020)
Observations	10,424,947	193,924
Adjusted R^2	0.019	0.948
Year-Month FE	Yes	Yes
Location FE	Yes	Yes

Note: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.3. Heterogeneity Analyses

Having documented robust average effects of AI-generated visuals on matching efficiency and transaction prices, we next examine heterogeneity in treatment effects to further shed light on the underlying mechanisms. In particular, from the perspective of the information frictions alleviation channel, we study whether the impact of AI Visual is stronger in settings where buyers face greater difficulty in forming beliefs about a property's latent post-renovation state.

5.3.1. Effects by Renovation Conditions We begin with heterogeneity by renovation condition, which provides the most direct test of the information frictions alleviation channel. Properties in poor renovation condition generally have lower baseline attractiveness and, more importantly, exhibit a larger gap between their current observable state and their relevant decision state (i.e., the post-renovation condition). As a result, buyers must rely heavily on mental simulation to infer the property's future value, thereby leading to greater uncertainty and higher cognitive costs.

In such settings, AI-generated post-renovation visuals can help reduce this information gap by providing a concrete and standardized representation of the property's potential future state. By partially externalizing the mental simulation process, these visuals facilitate belief formation and reduce the uncertainty associated with evaluating renovation outcomes. By contrast, for fully renovated properties, the relevant decision state is largely observable, leaving less scope for AI Visual to provide additional informational value.

To test this, we introduce an indicator variable, $Poor\_Renovated$, which equals one if a property is recorded as being in poor renovation condition, and zero otherwise, and interact it with $PostTreat$ in Equation (1).[20] The estimation results reported in Columns (1) and (2) of Table 4 show that the interaction term is negative and statistically significant, indicating a larger reduction in days on market for such properties. Column (3) further shows that the price effect is also stronger for poorly renovated properties. Taken together, these findings are consistent with the information frictions alleviation channel, as the treatment effect is more pronounced in settings where the gap between the current observable state and the relevant decision state is largest.

In addition, this pattern is less consistent with a generic "enhanced visual presentation" explanation. In our setting, AI-generated visuals do not replace the original property images or VR; rather, they are presented alongside the actual property condition, which remains fully observable to buyers. As such, the role of AI Visual is not to cosmetically improve the perceived current state of the property, but to provide additional information about its potential future state. This feature limits the extent to which simple visual appeal or presentation effects can account for the observed heterogeneity.

5.3.2. Effects by Market Thickness We next examine heterogeneity by market thickness. Prior literature suggests that while greater market thickness increases the number of available options, it can also intensify search frictions in online two-sided markets (Li and Netessine 2020). As the choice set expands, buyers face greater cognitive burdens in comparing alternatives, making it more difficult to evaluate each property's latent value and post-renovation potential.

In our context, thicker markets are characterized by more severe information frictions in the belief formation process. AI-generated future-state visuals can help mitigate these frictions by reducing the cognitive cost of evaluating each option and facilitating more efficient comparison across a larger set of properties. As a result, the positive impact of AI Visual may be amplified in environments with greater market thickness.

To test this, we construct a measure of market thickness, Mkt_Thic, defined as the logarithm of the average number of listed properties of the same housing type in the neighborhood during the three-month pre-treatment period, and interact it with $PostTreat$. The results in Columns (1) to (3) of Table 5 show that the coefficients on the interaction term are directionally consistent with the estimated coefficient on $PostTreat$ and are statistically significant, meaning that Mkt_Thic

[20] In the platform's system, properties classified as being in poor renovation condition refer to those with substandard interior finishes or unfinished (bare-shell) units.

Table 4 Heterogeneity of AI Effects by Renovation Level

	(1) Log(Buyer_days)	(2) Log(Seller_days)	(3) Log(Price)
PostTreat	-0.0903***	-0.2029***	0.0236***
	(0.023)	(0.030)	(0.006)
Poor_Renovated	0.0560**	0.0375	-0.1225***
	(0.024)	(0.024)	(0.012)
PostTreat × Poor_Renovated	-0.0330**	-0.0339**	0.0078*
	(0.016)	(0.013)	(0.004)
Building Size	0.0045***	0.0058***	-0.0010***
	(0.000)	(0.000)	(0.000)
Building Age	-0.0367*	0.0239***	-0.0040**
	(0.019)	(0.007)	(0.002)
Floor	-0.0020	0.0231***	-0.0085***
	(0.004)	(0.008)	(0.002)
Renovation	0.0027	-0.1034***	-0.0374***
	(0.019)	(0.018)	(0.006)
Rooms	0.0476***	-0.0671***	0.0347***
	(0.009)	(0.013)	(0.007)
Subway	0.0120	-0.0076	0.0141***
	(0.011)	(0.007)	(0.005)
Constant	2.2267***	3.9633***	10.4228***
	(0.070)	(0.069)	(0.022)
Observations	193,924	193,924	193,924
Adjusted R^2	0.123	0.077	0.946
Year-Month FE	Yes	Yes	Yes
Location FE	Yes	Yes	Yes

Note: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

positively moderates the main effect. These findings are consistent with the information frictions alleviation channel, as the benefits of AI-generated visuals are larger in environments where the future-state-related evaluation task is more complex. [21]

5.3.3. Effects by Agents' Performance We further examine heterogeneity across agents with different performance levels. In our setting, real estate agents serve as intermediaries who facilitate information transmission between buyers and sellers, particularly in interpreting property attributes and conveying latent value.

Lower-performing agents are likely to be less effective in helping buyers form accurate beliefs about a property's post-renovation potential, especially when such evaluation requires substantial inference. This may exacerbate information frictions in the matching process. AI-generated future-state visuals can help reduce these frictions by providing a standardized representation of future outcomes, thereby reducing reliance on agent-specific capabilities in conveying property

[21] While this pattern aligns with the information frictions interpretation, we interpret this heterogeneity with caution and view it as supportive rather than definitive evidence for the information frictions alleviation channel, as we cannot rule out alternative factors that may also contribute to this pattern.

Table 5 Heterogeneity of AI Effects by Market Thickness

	(1) Log(Buyer_days)	(2) Log(Seller_days)	(3) Log(Price)
PostTreat	-0.0722***	-0.1842***	0.0224***
	(0.024)	(0.037)	(0.008)
Mkt_thic	0.0228***	-0.0320***	-0.0077***
	(0.003)	(0.004)	(0.001)
PostTreat × Mkt_thic	-0.0124***	-0.0131*	0.0018*
	(0.005)	(0.008)	(0.001)
Building Size	0.0046***	0.0055***	-0.0009***
	(0.000)	(0.000)	(0.000)
Building Age	-0.0356*	0.0224***	-0.0045**
	(0.019)	(0.007)	(0.002)
Floor	-0.0019	0.0225***	-0.0083***
	(0.004)	(0.008)	(0.002)
Renovation	-0.0307***	-0.1229***	0.0493***
	(0.007)	(0.009)	(0.003)
Rooms	0.0411***	-0.0550***	0.0374***
	(0.009)	(0.013)	(0.007)
Subway	0.0131	-0.0085	0.0128**
	(0.010)	(0.007)	(0.005)
Constant	2.2862***	4.0955***	10.1626***
	(0.039)	(0.038)	(0.021)
Observations	193,924	193,924	193,924
Adjusted R^2	0.124	0.078	0.946
Year-Month FE	Yes	Yes	Yes
Location FE	Yes	Yes	Yes

Note: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

potential. By contrast, high-performing agents—who possess stronger domain knowledge and experience—may already be effective at mitigating such information gaps. As a result, the incremental value of AI-generated visuals is expected to be smaller for these agents.

To examine this, we use the platform's pre-treatment performance score, $Performance$, and interact it with $PostTreat$. The estimation results are presented in Table 6. In Columns (1) and (2), the coefficients on the interaction term are positive and statistically significant. Given that the baseline treatment effect reduces days on market, the positive interaction term implies that the magnitude of this reduction is attenuated for higher-performing agents. In Column (3), the coefficient on the interaction term is negative and statistically significant, indicating that the price-enhancing effect of AI Visual is also weaker for higher-performing agents. These findings are consistent with the notion that AI Visual primarily facilitates transaction outcomes by reducing information frictions in belief formation, particularly in settings where such frictions are more severe. [22]

[22] As with market thickness, heterogeneity along this dimension may also capture other factors, such as differences in agent effort, so we cautiously interpret it as complementary evidence rather than a standalone test of the mechanism.

Table 6 Heterogeneity of AI Effects by Agents' Performance

	(1) Log(Buyer_days)	(2) Log(Seller_days)	(3) Log(Price)
PostTreat	-0.1496***	-0.2599***	0.0321***
	(0.032)	(0.037)	(0.006)
Performance	-0.0194***	-0.0115***	-0.0001
	(0.003)	(0.004)	(0.000)
PostTreat × Performance	0.0132**	0.0124**	-0.0014**
	(0.006)	(0.006)	(0.001)
Building Size	0.0045***	0.0057***	-0.0009***
	(0.000)	(0.000)	(0.000)
Building Age	-0.0368*	0.0240***	-0.0041**
	(0.019)	(0.007)	(0.002)
Floor	-0.0021	0.0230***	-0.0082***
	(0.004)	(0.008)	(0.002)
Renovation	-0.0305***	-0.1231***	0.0493***
	(0.007)	(0.009)	(0.003)
Rooms	0.0477***	-0.0670***	0.0350***
	(0.009)	(0.013)	(0.007)
Subway	0.0125	-0.0072	0.0131**
	(0.011)	(0.007)	(0.005)
Constant	2.4030***	4.0696***	10.1465***
	(0.037)	(0.040)	(0.020)
Observations	193,924	193,924	193,924
Adjusted R^2	0.124	0.077	0.946
Year-Month FE	Yes	Yes	Yes
Location FE	Yes	Yes	Yes

Note: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.3.4. Effects by Buyers' Gender and Age Finally, we also explore whether the effects of AI Visual vary across buyer characteristics, specifically gender and age, which may proxy for differences in experience and information processing ability. Prior literature has documented gender disparities in housing transaction outcomes, raising the question of whether AI-generated visuals can reduce such differences by standardizing information presentation (Goldsmith-Pinkham and Shue 2023).

To examine this, we include a variable *Buyer_Gender*, which equals one if the buyer is male and zero otherwise, along with its interaction term with *PostTreat*. As reported in Appendix Table EC.6, the estimated coefficients on the interaction terms across Columns (1)–(3) are statistically insignificant. This suggests that AI-generated visuals do not differentially affect male and female buyers, consistent with the interpretation that the technology reduces information gaps in a relatively uniform manner across gender groups. We also examine heterogeneity by agent gender and find no statistically significant differences (Appendix Table EC.5).

We next explore heterogeneity across buyers' age groups. Buyer experience is likely to play an important role in determining the extent of information frictions faced during the search and evaluation process. Less experienced buyers—who are more likely to be younger—may have greater difficulty envisioning a property's post-renovation state and therefore face larger information gaps. In contrast, more experienced buyers are better able to infer property potential based on existing information.

Due to home-purchase restrictions in China during our sample period and data limitations, we are unable to directly observe buyers' prior purchasing experience. However, younger buyers are less likely to have prior homeownership experience. Therefore, buyer age serves as a reasonable proxy for buyer experience. We proxy for buyer experience using age. Specifically, we construct a discrete age variable ranging from 1 to 6, corresponding to age groups from below 20 to above 60, and include its interaction with $PostTreat$. The results reported in Appendix Table EC.7 show that the interaction terms in Columns (2) and (3) are statistically significant and opposite in sign to the baseline treatment effect. This indicates that the impact of AI Visual is stronger for younger (less experienced) buyers. These findings provide further support for the information frictions alleviation channel, as the benefits of AI-generated visuals are concentrated among buyers who face greater difficulty in forming accurate beliefs about a property's future state.

6. Further Analyses on Matching Quality

Thus far, we have provided empirical evidence on how AI Visual affects two primary matching outcomes (i.e., matching efficiency and transaction prices) along with mechanism tests from both the supply and demand sides as well as heterogeneity analyses. Nevertheless, relatively little is known about how AI Visual influences matching quality, another important dimension of market outcomes. Because consumers' perceptions of matching quality directly shape platform reputation and long-run operational performance, it is also crucial to understand the net effect of AI Visual on matching quality.

6.1. Effects on Post-transaction Perception of Matching Quality

Theoretically, the impact of AI Visual on buyers' post-transaction perceptions of matching quality is ambiguous. On the one hand, as documented in Section 5, AI-generated future-state visuals reduce information frictions and search costs, thereby improving matching efficiency. These efficiency gains should increase buyer utility and, in principle, improve perceived matching quality. On the other hand, the same technology may also introduce a secondary mechanism that adversely affects buyers' post-transaction evaluations.

Specifically, AI-generated future-state visuals may present an overly optimistic representation of a property's potential state (hereafter, the *over-optimistic representation channel*). By making future outcomes more salient and visually appealing, these representations can lead buyers to form overly optimistic beliefs about the realized post-transaction experience. Based on expectation disconfirmation theory, when the actual outcome falls short of the visually presented potential, buyers may experience negative disconfirmation, resulting in lower post-transaction satisfaction (Guan et al. 2023). In addition, if buyers attribute part of the transaction price increase to the influence of AI Visual, the price effect may further reduce their post-transaction perceived surplus. These countervailing forces introduce a fundamental ambiguity in how AI Visual affects buyers' perceptions of matching quality.

In contrast, the impact of AI Visual on sellers' perceptions of matching quality is conceptually more straightforward. For sellers, matching quality is primarily determined by transaction outcomes—such as transaction prices and days on market—rather than by post-transaction experiential reassessment. Since AI Visual improves both matching efficiency and transaction prices, we expect it to unambiguously enhance sellers' perceptions of matching quality.

Unlike matching efficiency, matching quality in two-sided markets is inherently difficult to measure objectively. Consistent with prior literature, we use post-transaction satisfaction from both buyers and sellers as proxies for matching quality (Zhao et al. 2024). An advantage of this measure is that it comprehensively captures both sides' subjective evaluations of matching quality. On the partner platform, buyers and sellers can provide discrete ratings ranging from 1 to 5 upon completing a transaction.[23]

We replace the dependent variable in Equation (1) with buyer ratings and seller ratings, respectively, and re-estimate the model. The results are reported in Table 7. In Column (1), the estimated coefficient on $PostTreat$ is -0.1703 ($p < 0.01$), indicating that AI Visual significantly reduces buyer ratings by 3.52% (0.1703 / 4.8435) relative to the pre-treatment mean. In Column (2), the coefficient on $PostTreat$ is 0.1812 ($p < 0.01$), suggesting that AI Visual significantly increases seller ratings by 3.88% (0.1812 / 4.6702). Figure EC.3 presents the event-study results for buyer and seller ratings. The pre-treatment coefficients are statistically indistinguishable from zero, suggesting that the parallel trends assumption largely holds. Taken together, these findings indicate that although AI Visual improves sellers' perceptions of matching quality, it negatively affects buyers' perceptions of matching quality, which is broadly consistent with our theoretical predictions.

6.2. Underlying Channels

We next examine the mechanism underlying the negative effect on buyers' post-transaction satisfaction. Given that Section 5 has established that AI Visual improves transaction efficiency and increases transaction prices—both of which benefit sellers—we focus here on testing the over-optimistic representation channel grounded in expectation disconfirmation theory.

[23] To address potential selection concerns in observed ratings, we examine whether the introduction of AI Visual changes the observable composition of transactions that appear in the review sample. We find no systematic evidence of compositional shifts along buyer, agent, or property characteristics, suggesting that observable selection into rated transactions is unlikely to drive our main results.

Table 7 Effects of AI Visual on Post-transaction Satisfaction of Buyers and Sellers

	(1) Rating(buyer)	(2) Rating(seller)
PostTreat	-0.1703***	0.1812***
	(0.016)	(0.018)
Building Size	-0.0002	0.0002
	(0.000)	(0.000)
Building Age	-0.0003	-0.0056
	(0.006)	(0.011)
Floor	-0.0011	0.0010
	(0.003)	(0.006)
Renovation	0.0048	-0.0032
	(0.004)	(0.007)
Rooms	0.0066	-0.0025
	(0.006)	(0.010)
Subway	0.0105*	0.0007
	(0.005)	(0.009)
Constant	4.8296***	4.6732***
	(0.016)	(0.033)
Observations	36,288	14,820
Adjusted R^2	0.068	0.100
Year-Month FE	Yes	Yes
Location FE	Yes	Yes

Note: Robust standard errors are reported in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In our setting, AI-generated future-state visuals provide a stylized and enhanced depiction of a property's post-renovation potential. If buyers rely on these visuals when forming beliefs, they may develop overly optimistic expectations prior to purchase. After the transaction, as buyers accumulate actual usage experience, they are able to reassess the realized property condition relative to the visually presented potential. When the realized outcome falls short of these optimistic beliefs, expectation disconfirmation occurs, leading to a decline in perceived matching quality (Guan et al. 2023).

If this mechanism is at work, the negative effect of AI Visual on buyer ratings should be primarily driven by buyers who have had sufficient time to experience the property before leaving feedback, rather than by those who submit ratings immediately after the transaction. This is because expectation disconfirmation requires post-transaction experience; thus, buyers need adequate time to form a realized assessment of the property. To test this prediction, we measure buyers' post-transaction experience duration as the time interval between transaction completion and the submission of a rating (i.e., Δdays). That is, buyers with shorter Δdays are less likely to have sufficient time to experience expectation disconfirmation, whereas those with greater Δdays are more likely to do so.

We therefore conduct a moderating effect analysis by treating Δdays as a continuous variable and including its interaction with *PostTreat*. The estimation results, reported in Table 8, show that the interaction term is negative and statistically significant for buyer ratings (see Column (1)), but insignificant for seller ratings (see Column (2)). These findings indicate that a longer post-transaction experience horizon amplifies the negative effect of AI Visual on buyer satisfaction, whereas no such pattern is observed on the seller side. This pattern is consistent with our prediction that the decline in buyers' perceived matching quality is driven by those who have accumulated sufficient post-transaction experience to reassess the property. In contrast, sellers' post-transaction satisfaction is primarily determined by transaction outcomes—such as price and time on market—rather than by experiential reassessment of the matched counterparty. Hence, these results provide evidence consistent with the over-optimistic representation channel, grounded in expectation disconfirmation theory: as buyers gain real usage experience, they update their beliefs and recognize the gap between the visually presented potential and the realized outcome, leading to lower satisfaction.

Because the overall rating mainly reflects buyers' comprehensive post-transaction evaluation of matching quality, it may capture multiple dimensions of satisfaction. However, expectation disconfirmation more directly concerns buyers' reassessment of whether the recommended property truly matched their preferences. Fortunately, in addition to the overall rating, the platform's review system includes optional structured tags, one of which evaluates whether the property recommendation was accurate. Buyers can select this tag after submitting their overall rating, thereby explicitly indicating their view on recommendation precision.

We therefore replace the dependent variable with *Recommend_optimal*, an indicator capturing whether the buyer endorses the accuracy of the recommendation, and re-estimate the regressions. The results, reported in Appendix Table EC.8, are largely consistent with those based on overall ratings. Column (2), which augments the baseline specification in Column (1) by introducing the interaction term, reports the moderating effect. The estimates show that the negative impact of AI Visual becomes more pronounced as post-transaction experience increases, consistent with the pattern observed in the main analysis. These findings provide additional evidence for the over-optimistic representation channel grounded in expectation disconfirmation theory, which is consistent with the notion that buyer dissatisfaction arises from belief updating after sufficient post-transaction experience.

Finally, we also conduct an additional placebo test to further validate the use of overall ratings as a proxy for perception of matching quality. In the platform's review system, buyers also can evaluate agents on dimensions including appearance and clarity of explanation, which should not be affected by AI Visual. We introduce two dependent variables—*Appearance* and *Intro_well*—and re-estimate Equation (1). The results, reported in Appendix Table EC.9, show that the coefficients on $PostTreat$ are statistically insignificant in both Columns (1) and (2). This placebo test supports the validity of our interpretation, suggesting that AI Visual does not systematically influence unrelated aspects of post-transaction evaluations.

Taken together, the evidence indicates that AI-generated future-state visuals introduce an efficiency–quality trade-off in two-sided markets. While they reduce information frictions and improve matching efficiency, they can also distort belief formation through over-optimistic representations, leading to lower post-transaction satisfaction for buyers.

Table 8 Moderating Effects of Post-Transaction Experience Duration

	(1) Rating (Buyer)	(2) Rating (Seller)
PostTreat	-0.1400***	0.1849***
	(0.016)	(0.019)
Δdays	-0.0009*	-0.0001
	(0.000)	(0.000)
PostTreat*Δdays	-0.0102***	-0.0003
	(0.002)	(0.001)
Building Size	-0.0001	0.0002
	(0.000)	(0.000)
Building Age	-0.0013	-0.0056
	(0.006)	(0.011)
Floor	-0.0009	0.0011
	(0.003)	(0.006)
Renovation	0.0036	-0.0032
	(0.004)	(0.007)
Rooms	0.0071	-0.0022
	(0.006)	(0.010)
Subway	0.0103*	0.0006
	(0.005)	(0.009)
Constant	4.8338***	4.6731***
	(0.016)	(0.033)
Observations	36,288	14,820
Adjusted R^2	0.084	0.100
Year-Month FE	Yes	Yes
Location FE	Yes	Yes

Note: Here, Δ days refers to the number of days of delay between transaction completion and rating submission. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6.3. Potential Prescription Strategies

So far, we find that although AI Visual improves overall matching outcomes—reflected in enhanced matching efficiency and improved seller-side perceptions of matching quality—it also generates a backfire effect on buyers' post-transaction evaluations. In this subsection, we explore potential prescriptive strategies to mitigate this unintended consequence.

Our earlier analysis suggests that this backfire effect operates through an over-optimistic representation channel. By presenting stylized and enhanced depictions of a property's future state, AI-generated visuals may lead buyers to form overly optimistic beliefs about post-transaction outcomes. While such representations facilitate decision-making ex ante by reducing information frictions, they may also obscure certain drawbacks or exaggerate latent property attributes. As buyers update their beliefs after experiencing the property, discrepancies between visually induced expectations and realized outcomes can generate negative disconfirmation, thereby lowering post-transaction satisfaction.

In this context, real estate agents play a central intermediary role in shaping buyer decisions. Agents' experience and domain knowledge may help mitigate such distortions by guiding buyers toward a more accurate assessment of property attributes and by providing corrective information when AI-generated visuals induce overly optimistic beliefs. However, agents differ substantially in their capabilities. Lower-performing agents may lack the expertise necessary to counterbalance AI-induced distortions, whereas higher-performing agents may be better positioned to interpret, contextualize, and supplement AI-generated information.

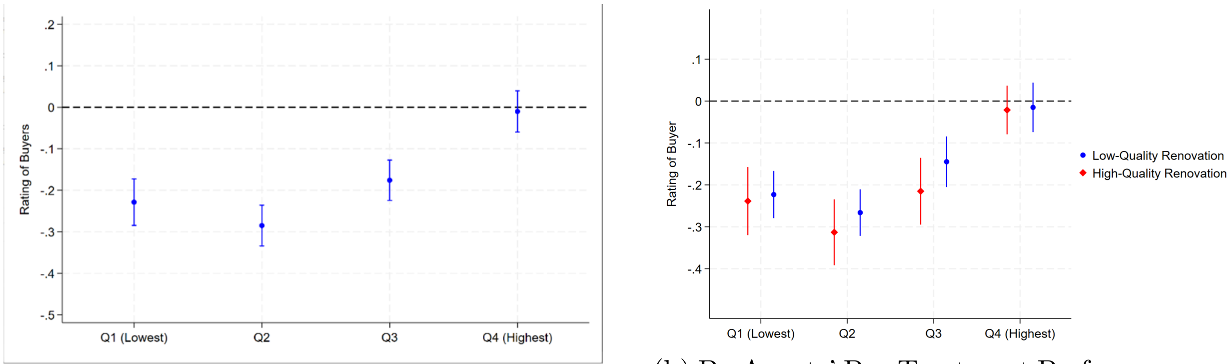
To examine this mechanism, we investigate whether the negative effect of AI Visual on buyers' perceptions of matching quality varies across agents with different performance levels. Specifically, we classify agents into quartiles based on their pre-treatment performance scores: Q1 (lowest), Q2 (lower-middle), Q3 (upper-middle), and Q4 (highest). We then conduct subgroup regressions. The results, presented in Panel (a) of Figure 2, show that the negative effect of AI Visual on buyers' perceptions of matching quality disappears when transactions are handled by top-performing agents (Q4). In contrast, the negative response is more pronounced when transactions are handled by lower-performing agents (Q1 and Q2). Combined with the estimation results reported in Appendix Table EC.10, we find that for transactions handled by high-performing agents, AI Visual continues to significantly improve matching efficiency: it reduces sellers' days on market by approximately 20% and buyers' days on market by about 7.9%. These findings suggest that high-performing agents' experience and domain knowledge can serve as an effective buffer against the backfire effect induced by AI Visual, while simultaneously preserving substantial efficiency gains from the technology. More broadly, this pattern suggests that human expertise can act as a corrective complement to AI-generated information. While AI Visual improves ex ante decision-making by making latent future states more salient, experienced agents can help buyers interpret these visuals more realistically, correct overly optimistic beliefs, and align expectations with feasible post-transaction outcomes.

While this pattern is consistent with the interpretation that high-performing agents mitigate the over-optimistic representation channel through expertise and domain knowledge, one concern is that alternative explanations may also contribute. For instance, higher-performing agents may have access to better property portfolios and match with different types of buyers. To address these concerns, our empirical design leverages pre-treatment performance measures and rich fixed effects to absorb systematic differences across agents and listings. Moreover, the fact that the moderating effect operates specifically on post-transaction satisfaction—rather than on baseline matching efficiency alone—is more consistent with a mechanism related to belief correction and expectation management than with purely operational advantages.

To further address the concern that higher-performing agents may have access to superior property portfolios or systematically match with different types of buyers—thereby mechanically sustaining higher post-transaction satisfaction—we examine whether this moderating effect persists across properties with different renovation quality. Splitting the sample into low- and high-quality renovation groups, we find that high-performing agents attenuate the negative effect of AI Visual in both sub-samples (see Panel (b) of Figure 2). In addition, we further conduct subgroup analyses along key buyer and property characteristics. The results, presented in Appendix Figure EC.4, show that when transactions are handled by high-performing agents, the backfire effect is effectively mitigated across different types of buyers and property categories. These patterns suggest that the mitigating role of agent expertise is not limited to specific buyer/property types, but instead reflects a broader ability to correct AI-induced distortions in buyer belief formation. Taken together, these findings provide suggestive evidence that agent expertise can partially offset the adverse effects of AI-generated visuals on buyer satisfaction by mitigating the over-optimistic representation channel. While we do not fully disentangle all potential mechanisms, the results highlight the importance of human–AI complementarities in two-sided markets.

This prescription analysis yields several managerial implications. First, platforms that place weight on long-term buyer satisfaction may benefit from a more targeted deployment of AI Visual, particularly in settings where agents possess sufficient expertise to contextualize and interpret AI-generated information. Second, investing in training programs that enhance agents' domain knowledge and advisory capabilities may improve their ability to manage buyer expectations and reduce AI-induced mismatches. Third, platform designers should account for the risk that AI-generated visuals may systematically overstate property potential. Incorporating design features that provide more balanced representations—such as highlighting uncertainty, constraints, or alternative scenarios—may help mitigate the backfire effect while preserving the efficiency gains from reduced information frictions.

Figure 2 Heterogeneous Effects of AI Visual on Buyers' Ratings by Agents' Pre-Treatment Performance



(a) By Agents' Pre-Treatment Performance

(b) By Agents' Pre-Treatment Performance and Renovation Level

7. Robustness Checks

In this section, we conduct a comprehensive set of robustness checks to further validate our main findings. We begin by addressing potential treatment misclassification by excluding listings whose listing periods span the roll-out, ensuring a clean separation between treated and control observations. We then examine whether the roll-out induces compositional changes in transacted listings or reviewed samples, alleviating concerns that our results are driven by selection rather than treatment effects. Next, we address methodological concerns in staggered DiD settings by adopting alternative estimators that are robust to treatment effect heterogeneity across cohorts and over time. We further mitigate omitted variable concerns by incorporating additional district-level economic controls. We also verify that our results are robust to alternative measures of matching outcomes and alternative clustering strategies. Finally, we provide supporting evidence for the exogeneity of roll-out timing by showing that local housing market characteristics do not predict the deployment of AI Visual.

7.1. Excluding Listings Spanning the roll-out Period

A remaining concern is that some listings may be classified as treated even though they were listed prior to the roll-out and transacted afterward. For these listings, exposure to AI Visual is partial, which may introduce measurement error in treatment assignment. While such misclassification would likely attenuate the estimated effects, it may still raise concerns about the interpretation of the results.

To address this issue, we construct a more conservative sample by excluding listings whose listing period spans the roll-out date. This restriction ensures that all remaining listings are either fully untreated or fully exposed to AI Visual throughout their lifecycle. Re-estimating Equation (1) using this restricted sample, we find that the estimation results remain consistent with our baseline estimates (see Appendix Table EC.11). This suggests that our findings are not driven by partial treatment exposure or timing misclassification.

7.2. Compositional Stability of Transacted Listings

A potential concern is that the roll-out of AI Visual may change the composition of transacted listings. For example, if the feature affects which properties are more likely to transact, the observed increase in transaction prices may partly reflect selection into sale rather than a pure valuation or treatment effect. A similar concern applies to matching efficiency: reductions in days on market may arise from compositional shifts in transacted listings rather than true acceleration of comparable matches.

To address this concern, we examine whether the characteristics of transacted properties systematically change following the roll-out. Specifically, we replace the dependent variable with key property attributes—including number of rooms, building size, renovation level, and proximity to subway etc.—and re-estimate Equation (1). The results, reported in Appendix Table EC.12, show no statistically significant changes in these characteristics following the introduction of AI Visual.[24] These findings suggest that the roll-out does not materially alter the composition of transacted listings, alleviating concerns that our main results are driven by selection effects rather than changes in matching outcomes.

7.3. Alternative DiD Estimators

Recent literature has shown that in staggered DiD settings, conventional two-way fixed effects (TWFE) estimators may produce biased estimates when treatment effects are heterogeneous across adoption cohorts or over time. To address this concern, we re-estimate our models using the estimators proposed by Callaway and Sant'Anna (2021), Borusyak et al. (2024), which are robust to such heterogeneity. The results are reported in Appendix Table EC.17. Across Columns (1)–(5), the estimated treatment effects remain consistent with our baseline findings. These results suggest that our conclusions are not driven by the potential biases associated with the TWFE estimator in staggered adoption settings.

7.4. Additional Controls: Regional-Level Economic Indicators

A potential concern is that time-varying district-level economic conditions may simultaneously affect both the timing of AI Visual adoption and matching outcomes, thereby confounding our estimates. To address this issue, we augment our baseline specification by including quarterly district-level economic indicators, such as GDP and unemployment rates, as additional controls. The estimation results, presented in Appendix Table EC.13, show that the coefficient on $PostTreat$ remains stable in magnitude and statistical significance. This finding alleviates concerns that omitted district-level time-varying factors drive our main results.

[24] At the renovation level, it is only significant at the 10% level.

7.5. Clustered Standard Errors

In our baseline specification, we cluster standard errors at the district level to account for potential correlation in the error terms among properties within the same district. Clustering at the district level relaxes the assumption of independent errors across observations within a district and helps avoid downward-biased standard errors. As a robustness check, we adopt a more stringent inference strategy by clustering standard errors two-way at the district and week levels. This approach allows for arbitrary correlation within districts over time as well as across districts within the same week. The latter dimension accounts for common time-specific factors—such as market-wide fluctuations or seasonal patterns—that may affect all properties in a given period. We then re-estimate Equation (1) under this two-way clustering structure. The estimated coefficients on $PostTreat$ shown in Appendix Table EC.14 remain quantitatively similar and statistically significant, consistent with our baseline results. These findings suggest that our conclusions are robust to more conservative clustering adjustments.

Since our sample includes a limited number of cities—raising potential concerns regarding inference under clustering—we cluster standard errors at the district level in our baseline specification to capture within-district correlation. Nevertheless, to ensure robustness, we implement more conservative clustering strategies. Specifically, we first cluster standard errors at the city level, which provides a more aggregated and conservative inference given that the roll-out occurs at the city level. In addition, we adopt a two-way clustering approach at the city and week levels to account for both spatial and temporal dependence in the error terms. This specification allows for arbitrary correlation within cities over time, as well as common shocks across cities within the same week. The estimation results, reported in Appendix Table EC.15 and Table EC.16, remain statistically significant and quantitatively similar to our baseline estimates. These findings suggest that our conclusions are robust to alternative and more conservative clustering choices.

7.6. Alternative Dependent Variables

We further examine whether our findings are robust to alternative measures of matching outcomes. In the baseline analysis, we use days on market for buyers and sellers as proxies for matching efficiency. As an alternative measure, we include an indicator variable equal to one if a listed property is sold within three months (Sold<3Month), and zero otherwise. Re-estimating Equation (1) with this alternative dependent variable, we find that the coefficient on $PostTreat$ remains positive and statistically significant (see Appendix Table EC.18), indicating that AI Visual indeed significantly improves matching efficiency. In addition, we use the last listed price of transacted properties as an alternative proxy for transaction prices. The results, reported in Column (2) of Appendix Table EC.18, remain consistent with our baseline estimates. Together, these findings confirm that our main results are robust to alternative outcome measures.

7.7. Selection into Review and Rating Behavior

A potential concern in our matching quality analysis is selection into the rating sample. The number of observed ratings is smaller than the total number of transactions (approximately 36,288 buyer ratings and 14,820 seller ratings versus roughly 194,000 transactions), raising the possibility that AI Visual may affect which types of transactions are more likely to generate reviews. If the composition of reviewed transactions changes systematically after the roll-out, our estimates of post-transaction satisfaction may be biased.

To address this concern, we examine whether AI Visual affects the key characteristics of transactions that appear in the review sample. Specifically, within the sample of transactions with observed ratings, we test whether the roll-out of AI Visual shifts the composition along key buyer, agent, and property dimensions. These include buyer demographics (e.g., gender and age), agent characteristics (e.g., gender and performance), and property attributes owned by sellers (e.g., number of rooms and other housing features). We implement this test by replacing the dependent variable in Equation (1) with each of these observable characteristics and estimating whether $PostTreat$ significantly predicts variation in these attributes. The estimation results, reported in Appendix Table EC.19, show that the coefficients on $PostTreat$ are uniformly small in magnitude and statistically insignificant across all examined characteristics. This indicates that the roll-out of AI Visual does not systematically alter the composition of reviewed transactions along observable dimensions. Taken together, these findings alleviate concerns that our results on post-transaction satisfaction are driven by selection into the rating sample.

7.8. Predicting Time of AI Introduction

Another concern is that certain local housing market characteristics may influence the platform's staggered roll-out of AI Visual across cities, potentially leading to endogenous treatment timing and reverse causality. Although the platform states that the timing of AI Visual adoption is unrelated to local housing market conditions, we formally test this claim.

Specifically, we construct a city-level panel dataset and estimate a linear probability model in which the dependent variable, $Whether\_introduced$, equals one if AI Visual is introduced in a given city-week and zero otherwise. The independent variables include a range of aggregated city-level housing market characteristics, such as average transaction prices, average time-to-sale, and property attributes. The results, reported in Appendix Table EC.20, show that none of these variables significantly predict the timing of AI Visual adoption. This evidence further supports the exogeneity of the roll-out and reinforces the validity of our staggered DiD identification strategy.

8. Conclusion

This study shows that AI-generated future-state visuals can serve as an important information design lever in two-sided markets. By making otherwise unobservable future states more concrete and salient, AI Visual changes how buyers form beliefs, evaluate alternatives, and make transaction decisions under uncertainty. Empirically, we find that this information design intervention significantly enhances matching efficiency and improves platform-level outcomes: it shortens days on market for both buyers and sellers and increases transaction prices. These findings suggest that AI-generated visuals function as a scalable and cost-effective information technology that improves market performance by alleviating information frictions on the demand side.

Meanwhile, our findings reveal an important trade-off between matching efficiency and post-transaction matching quality. While AI-generated future-state visuals improve transaction efficiency and increase seller-side outcomes, they may also introduce distortions in buyers' perceptions through an over-optimistic representation of a property's potential future state. When realized outcomes fall short of visually presented scenarios, buyers experience lower post-transaction satisfaction. This finding suggests that, beyond reducing information frictions, generative AI can also introduce new forms of behavioral frictions by systematically shifting buyers' beliefs in a biased direction. As such, the overall market implications of AI Visual deployment in two-sided markets depend not only on its ability to reduce uncertainty, but also on the accuracy and reliability of the information it provides.

These insights carry important managerial implications for platform design and governance. Rather than treating AI-generated visuals as a uniform interface enhancement, platforms should view them as an information design lever whose effects depend on the informational environment in which users make decisions. Targeting AI Visual to segments with high information frictions—such as poorly renovated properties, less experienced buyers, lower-performing agents, and thicker markets—can maximize efficiency gains. However, because the same information design lever may also induce overly optimistic beliefs, platforms should complement deployment with safeguards such as human expert guidance, uncertainty disclosure, or more balanced visual representations. One effective approach is to complement AI-generated visuals with human expertise. We document that high-performing agents can serve as corrective complements to AI-generated information: through their domain knowledge and communication skills, they contextualize AI-generated visuals, help buyers interpret future-state representations more realistically, and anchor buyer expectations around feasible post-transaction outcomes. In doing so, human expertise mitigates the buyer-side satisfaction backfire while preserving the efficiency gains generated by AI Visual. This highlights the importance of hybrid human–AI systems in which algorithmic tools and human intermediaries jointly shape outcomes in two-sided markets.

Taken together, our findings highlight the dual role of AI-generated future-state visuals as both a friction-reducing information technology and a potential source of belief distortions in two-sided markets. This duality implies that the successful integration of generative AI into platform design requires more than technological adoption alone. Instead, it calls for careful alignment between AI-generated information, user interpretation, and institutional safeguards. Platforms must therefore balance short-term efficiency gains with long-term matching quality by combining adaptive targeting strategies with human oversight.

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Online Appendix

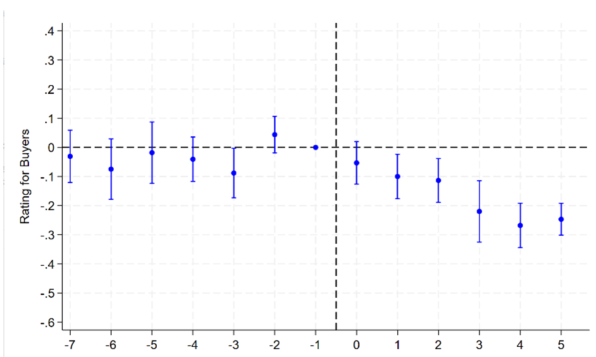
EC.1. Additional Table and Figure

Table EC.1 Sample Cities and Treatment Start Dates in Our Dataset

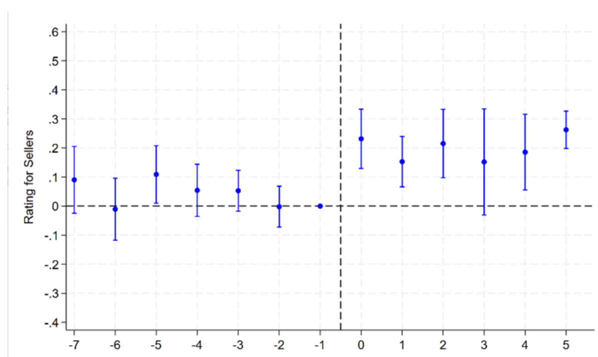
City ID	Pretreatment Average Days on Market (Sellers)	Treatment Start Date
1	123.26	October 15, 2020
2	130.34	October 15, 2020
3	99.35	October 15, 2020
4	97.22	January 18, 2021
5	140.60	January 18, 2021
6	107.60	January 18, 2021
7	120.73	January 18, 2021
8	148.43	May 13, 2021
9	104.91	May 13, 2021
10	101.24	May 13, 2021
11	84.36	August 4, 2021
12	94.66	August 4, 2021

Note: This table presents the anonymized city identifiers in our dataset and the corresponding treatment introduction dates for each roll-out batch. As required by our partner firm, the actual city names are kept confidential; therefore, we report anonymized city IDs along with the average seller days on market during the quarter prior to treatment.

Figure EC.3 Event Studies, Effects of AI Visual on Post-transaction Satisfaction of Buyers and Sellers



(a) Rating (Buyer)



(b) Rating (Seller)

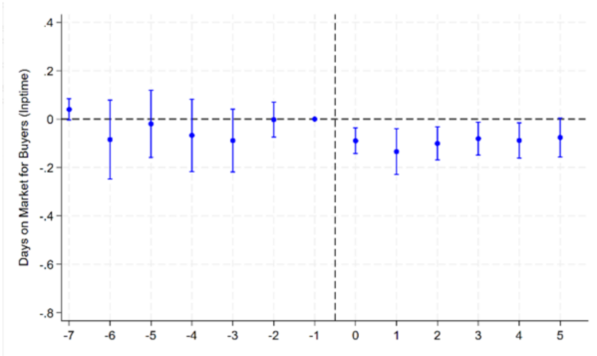
Note: This figure presents event-study estimates of the effects of AI Visual on post-transaction satisfaction of buyers and sellers. Panel (a) shows effects on buyers' ratings, and Panel (b) shows effects on sellers' ratings. Error bars represent 95% confidence intervals.

Table EC.2 Definition of Key Variables

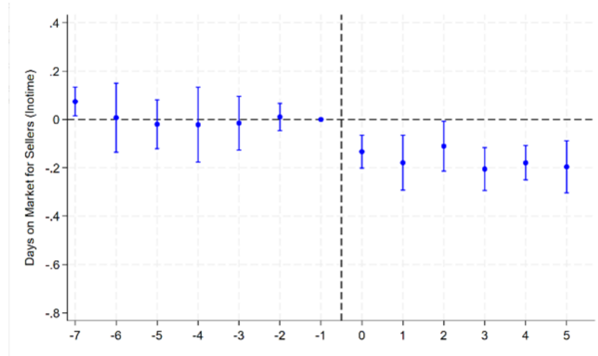
Variable	Definition
Log(Buyer_days)	Natural logarithm of buyers' time-on-market (transaction cycle from initial search to completion).
Log(Seller_days)	Natural logarithm of sellers' time-on-market (duration from listing to transaction completion).
Log(Price)	Natural logarithm of unit transaction price.
Log(Last listed Price)	Natural logarithm of the last listed unit price of the transacted property.
Sold<3months	Indicator equal to 1 if the listed property is sold within three months.
Viewing	Number of on-site viewings of the listed property in a given week.
Adjust_times	Number of price adjustments made by the seller for the listed property in a given week.
Adjust_mag	Magnitude of the seller's weekly price adjustment, measured as the percentage change relative to the previous listing price.
Rating(buyer)	Overall rating (1–5) submitted by buyers in the platform's review system.
Rating(seller)	Overall rating (1–5) submitted by sellers in the platform's review system.
Recommend_optimal	Indicator equal to 1 if the buyer selects the "accurate property recommendation" tag in the review system.
Appearance	Indicator equal to 1 if the buyer selects the "professional appearance" tag for the agent in the review system.
Intro_well	Indicator equal to 1 if the buyer selects the "clear property explanation" tag in the review system.
Poor_Renovated	Indicator equal to 1 if the property is classified by the platform as either minimally renovated or unfurnished.
Mkt_thic	Market thickness of listed properties, measured as the natural logarithm of the average number of listed properties of the same housing type in the corresponding neighborhood.
Performance	Agent performance score in the platform's internal evaluation system.
Agent_gender	Indicator equal to 1 if the agent is male, and 0 if female.
Buyer_gender	Indicator equal to 1 if the buyer is male, and 0 if female.
Buyer_age	Discrete buyer age variable ranging from 1 to 6, corresponding to age groups from below 20 to above 60.
Building Size	Property size measured in square meters.
Building Age	Age of the building.
Renovation	Renovation status (1 = unfurnished, 2 = basic renovation, 3 = fully renovated); used as a control variable.
Floor	Floor level (1 = low, 2 = middle, 3 = high).
Subway	Indicator equal to 1 if the property is located near a subway station, and 0 otherwise.
Rooms	Number of rooms in the property.

Note: This table reports the definitions of the variables used in the analysis. Summary statistics are presented in Table 1.

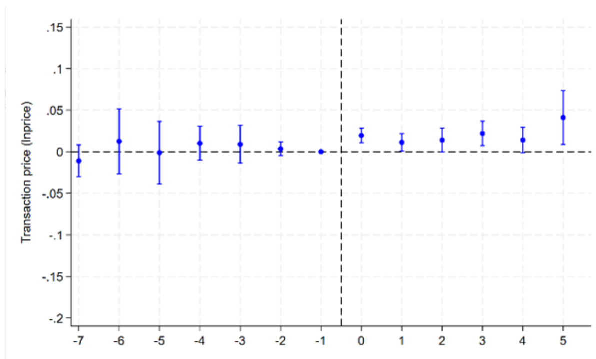
Figure EC.1 Event Studies, Effects of AI Visual on Matching Efficiency and Transaction Prices



(a) Days on Market for Buyers



(b) Days on Market for Sellers



(c) Transaction Prices

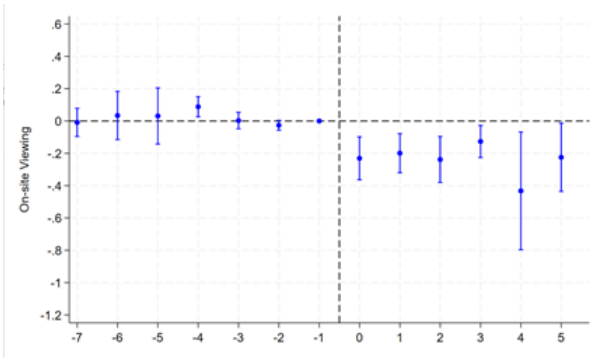
Note: This figure presents event-study estimates of the effects of AI Visual on matching efficiency and transaction prices. Panel (a) shows effects on buyers' days on market, Panel (b) shows effects on sellers' days on market, and Panel (c) shows effects on transaction prices. Error bars represent 95% confidence intervals.

Table EC.3 Supply-side: Effects of AI Visual on Sellers' Pricing Adjustment Behaviors

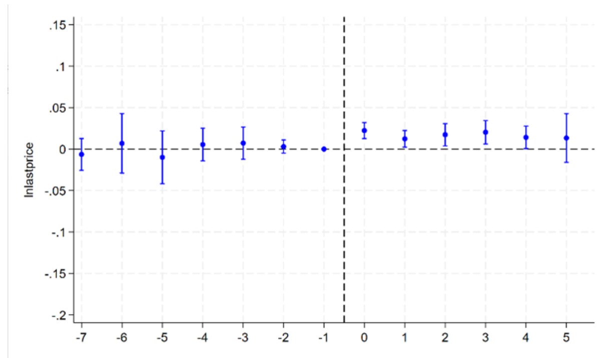
	(1) Adjust_times	(2) Adjust_mag
PostTreat	-0.0019	0.0487
	(0.006)	(0.037)
Building Size	0.0025*	-0.0198***
	(0.001)	(0.003)
Building Age	-0.0010	-0.0179***
	(0.001)	(0.003)
Floor	0.0050***	-0.0145***
	(0.001)	(0.003)
Renovation	0.0274***	-0.0527***
	(0.002)	(0.005)
Rooms	-0.0081***	0.0299***
	(0.002)	(0.006)
Subway	-0.0001	0.0057
	(0.001)	(0.004)
Constant	0.1496***	-0.3078***
	(0.006)	(0.020)
Observations	10,364,540	10,364,540
Adjusted R^2	0.027	0.021
Year-Month FE	Yes	Yes
Location FE	Yes	Yes

Note: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

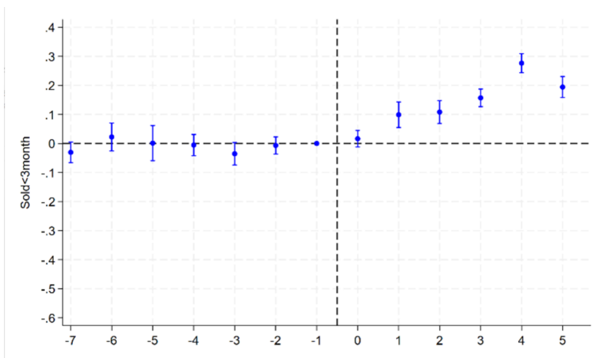
Figure EC.2 Event Studies, Effects of AI Visual on On-site Viewing, Last Listed Prices, and Sales within Three Months



(a) On-site Viewing



(b) Last Listed Prices



(c) Sales within Three Months

Note: This figure presents event-study estimates of the effects of AI Visual on on-site viewing, last listed prices, and whether listed properties transacted within three months. Error bars represent 95% confidence intervals.

Table EC.4 Effects of AI Visual on On-site Negotiation Ratio

VARIABLES	(1) On-site Negotiation Ratio (%)
PostTreat	-0.9032***
	(0.210)
Building Size	-0.0092**
	(0.004)
Building Age	0.2837***
	(0.048)
Floor	-0.0447**
	(0.020)
Renovation	0.0102
	(0.044)
Rooms	0.2040**
	(0.084)
Subway	-0.0006
	(0.035)
Constant	3.4685***
	(0.282)
Observations	193,924
Adjusted R-squared	0.077
Year-Month FE	Yes
Location FE	Yes

Note: This table presents estimates of the effects of AI Visual on the on-site negotiation ratio based on Eq. (1). The on-site negotiation ratio is defined as:

$$\text{On-site Negotiation Ratio} = \frac{\text{Last Listed Price} - \text{Transaction Price}}{\text{Last Listed Price}} \times 100\%. \tag{EC.1}$$

Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table EC.5 Heterogeneity of AI Effects by Agents' Gender

	(1) Log(Buyer_days)	(2) Log(Seller_days)	(3) Log(Price)
PostTreat	-0.1026***	-0.2223***	0.0254***
	(0.020)	(0.028)	(0.006)
Agent_gender	-0.0028	-0.0060	0.0004
	(0.008)	(0.008)	(0.001)
PostTreat × Agent_gender	-0.0030	0.0067	0.0026
	(0.017)	(0.016)	(0.002)
Building Size	0.0045***	0.0057***	-0.0009***
	(0.000)	(0.000)	(0.000)
Building Age	-0.0366*	0.0241***	-0.0041**
	(0.019)	(0.007)	(0.002)
Floor	-0.0021	0.0230***	-0.0082***
	(0.004)	(0.008)	(0.002)
Renovation	-0.0306***	-0.1232***	0.0493***
	(0.007)	(0.009)	(0.003)
Rooms	0.0476***	-0.0670***	0.0350***
	(0.009)	(0.013)	(0.007)
Subway	0.0125	-0.0073	0.0131**
	(0.011)	(0.007)	(0.005)
Constant	2.3387***	4.0347***	10.1458***
	(0.040)	(0.036)	(0.020)
Observations	193,924	193,924	193,924
Adjusted R^2	0.123	0.077	0.946
Year-Month FE	Yes	Yes	Yes
Location FE	Yes	Yes	Yes

Note: This table presents heterogeneity in the effects of AI Visual by agent gender. The variable *Agent_gender* equals one if the agent is male and zero otherwise. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table EC.6 Heterogeneity of AI Effects by Buyers' Gender

	(1) Log(Buyer_days)	(2) Log(Seller_days)	(3) Log(Price)
PostTreat	-0.1013***	-0.2207***	0.0282***
	(0.021)	(0.030)	(0.006)
Buyer_gender	-0.0335***	-0.0010	-0.0065***
	(0.010)	(0.006)	(0.001)
PostTreat × Buyer_gender	-0.0054	0.0059	-0.0015
	(0.015)	(0.012)	(0.002)
Building Size	0.0045***	0.0057***	-0.0009***
	(0.000)	(0.000)	(0.000)
Building Age	-0.0373**	0.0241***	-0.0042**
	(0.019)	(0.007)	(0.002)
Floor	-0.0018	0.0230***	-0.0081***
	(0.004)	(0.008)	(0.002)
Renovation	-0.0308***	-0.1232***	0.0493***
	(0.007)	(0.009)	(0.003)
Rooms	0.0497***	-0.0671***	0.0354***
	(0.009)	(0.013)	(0.007)
Subway	0.0122	-0.0072	0.0131**
	(0.011)	(0.007)	(0.005)
Constant	2.3499***	4.0312***	10.1486***
	(0.036)	(0.035)	(0.019)
Observations	193,924	193,924	193,924
Adjusted R^2	0.123	0.077	0.946
Year-Month FE	Yes	Yes	Yes
Location FE	Yes	Yes	Yes

Note: This table presents heterogeneity in the effects of AI Visual by buyer gender. The variable *Buyer_gender* equals one if the buyer is male and zero otherwise. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table EC.7 Heterogeneity of AI Effects by Buyers' Experiences

	(1) Log(Buyer_days)	(2) Log(Seller_days)	(3) Log(Price)
PostTreat	-0.1057***	-0.2879***	0.0488***
	(0.032)	(0.045)	(0.010)
Buyer_age	-0.0295***	-0.0330***	-0.0521***
	(0.008)	(0.006)	(0.004)
PostTreat × Buyer_age	0.0007	0.0208**	-0.0056***
	(0.007)	(0.009)	(0.002)
Building Size	0.0042***	0.0055***	-0.0014***
	(0.000)	(0.000)	(0.000)
Building Age	-0.0370*	0.0237***	-0.0049***
	(0.019)	(0.007)	(0.002)
Floor	-0.0017	0.0233***	-0.0075***
	(0.004)	(0.008)	(0.002)
Renovation	-0.0343***	-0.1268***	0.0426***
	(0.007)	(0.009)	(0.002)
Rooms	0.0574***	-0.0579***	0.0529***
	(0.008)	(0.013)	(0.005)
Subway	0.0142	-0.0057	0.0163***
	(0.010)	(0.007)	(0.005)
Constant	2.4442***	4.1510***	10.3357***
	(0.033)	(0.037)	(0.019)
Observations	193,924	193,924	193,924
Adjusted R^2	0.124	0.078	0.950
Year-Month FE	Yes	Yes	Yes
Location FE	Yes	Yes	Yes

Note: This table presents heterogeneity in the effects of AI Visual by buyers' past experience. Buyer age is used as a proxy for experience and is measured as a discrete variable ranging from 1 to 6, corresponding to age groups from below 20 to above 60. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table EC.8 Effects of AI Visual on Buyers' Post-Transaction Evaluations of Listing Recommendation Accuracy

	Recommend_optimal	Recommend_optimal (moderating)
	(1)	(2)
PostTreat	-0.0288*	-0.0193
	(0.017)	(0.018)
Δdays		-0.0013***
		(0.000)
PostTreat*Δdays		-0.0036***
		(0.001)
Building Size	-0.0000	-0.0000
	(0.000)	(0.000)
Building Age	-0.0037	-0.0046
	(0.004)	(0.004)
Floor	-0.0076***	-0.0075***
	(0.002)	(0.002)
Renovation	-0.0031	-0.0035
	(0.003)	(0.003)
Rooms	-0.0006	-0.0005
	(0.004)	(0.004)
Subway	-0.0005	-0.0006
	(0.005)	(0.005)
Constant	0.2854***	0.2907***
	(0.013)	(0.012)
Observations	36,288	36,288
Adjusted R^2	0.212	0.217
Year-Month FE	Yes	Yes
Location FE	Yes	Yes

Note: This table presents the effects of AI Visual on buyers' post-transaction evaluations of listing recommendation accuracy based on Eq. (1). Column (1) reports the baseline effect on *Recommend_optimal*, and Column (2) examines the moderating role of $\Delta days$. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table EC.9 Placebo Test: Effects of AI Visual on Buyers' Post-Transaction Evaluations of Agents' Professional Appearance and Explanation Clarity

	(1) Appearance	(2) Intro_well
PostTreat	-0.0296	0.0199
	(0.028)	(0.019)
Building Size	-0.0001	0.0002*
	(0.000)	(0.000)
Building Age	-0.0139***	-0.0026
	(0.005)	(0.004)
Floor	-0.0019	-0.0001
	(0.003)	(0.002)
Renovation	0.0009	-0.0010
	(0.004)	(0.003)
Rooms	0.0108**	-0.0041
	(0.005)	(0.003)
Subway	0.0027	0.0038
	(0.005)	(0.004)
Constant	0.3421***	0.2163***
	(0.019)	(0.010)
Observations	36,288	36,288
Adjusted R^2	0.215	0.273
Year-Month FE	Yes	Yes
Location FE	Yes	Yes

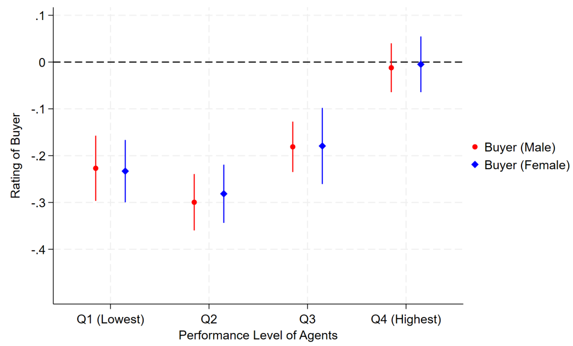
Note: This table presents placebo tests examining the effects of AI Visual on buyers' post-transaction evaluations of agents' professional appearance and explanation clarity, based on whether buyers select the corresponding evaluation tags. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table EC.10 Effects of AI Visual on Matching Efficiency and transaction prices: High-Performing Agents (Top Quartile)

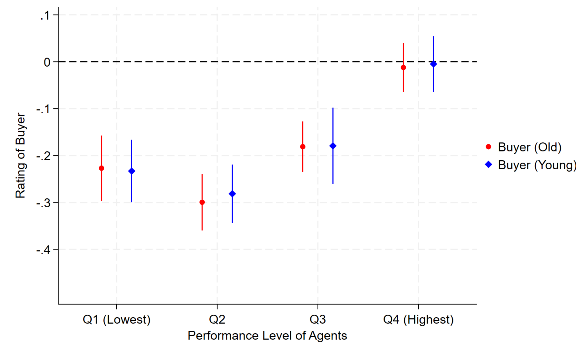
VARIABLES	(1) Log(Buyer_days)	(2) Log(Seller_days)	(3) Log(Price)
PostTreat	-0.0789***	-0.2016***	0.0261***
	(0.020)	(0.030)	(0.006)
Building Size	0.0042***	0.0057***	-0.0009***
	(0.000)	(0.000)	(0.000)
Building Age	-0.0524***	0.0421***	-0.0063**
	(0.017)	(0.012)	(0.003)
Floor	-0.0048	0.0289**	-0.0081***
	(0.009)	(0.011)	(0.002)
Renovation	-0.0420***	-0.1251***	0.0500***
	(0.014)	(0.013)	(0.003)
Rooms	0.0647***	-0.0778***	0.0357***
	(0.012)	(0.015)	(0.008)
Subway	0.0051	-0.0078	0.0113*
	(0.019)	(0.012)	(0.006)
Constant	2.3062***	4.0139***	10.1427***
	(0.060)	(0.038)	(0.021)
Observations	48,156	48,156	48,156
Adjusted R-squared	0.117	0.078	0.947
Year-Month FE	Yes	Yes	Yes
Location FE	Yes	Yes	Yes

Note: This table presents the effects of AI Visual on matching efficiency and transaction prices when the sample is restricted to transactions handled by high-performing agents (top quartile based on pre-treatment performance). Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

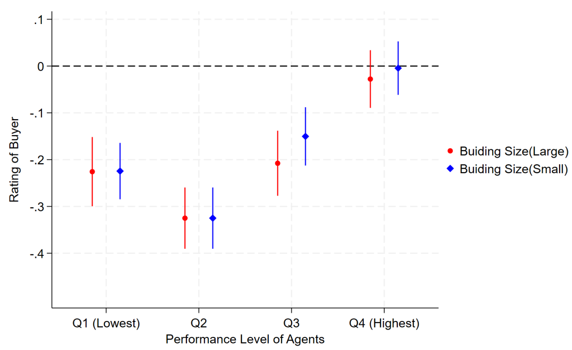
Figure EC.4 Heterogeneous Effects of AI Visual on Buyers' Ratings by Agents' Pre-Treatment Performance and Buyers (Properties) Characteristics



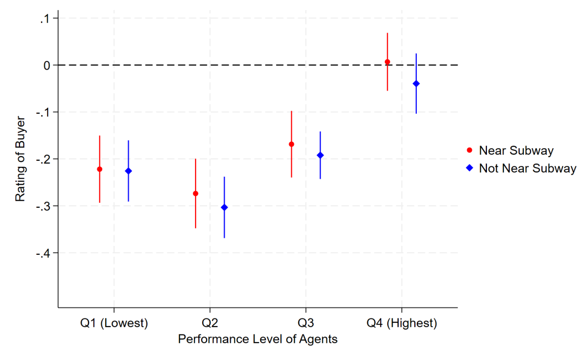
(a) By Agents' Pre-Treatment Performance and Buyers' Gender



(b) By Agents' Pre-Treatment Performance and Buyers' Age



(c) By Agents' Pre-Treatment Performance and Building Size



(d) By Agents' Pre-Treatment Performance and Near Subway

Note: This figure presents heterogeneous effects of AI Visual on buyers' ratings by agents' pre-treatment performance and buyer (property) characteristics. Error bars represent 95% confidence intervals.

Table EC.11 Robustness Check on Excluding Listings Spanning the roll-out Period

	(1) Log(Buyer_days)	(2) Log(Seller_days)	(3) Log(Price)	(4) Rating(buyer)	(5) Rating(seller)
PostTreat	-0.1077***	-0.4312***	0.0325***	-0.1827***	0.1888***
	(0.019)	(0.025)	(0.006)	(0.017)	(0.018)
Building Size	0.0046***	0.0053***	-0.0009***	-0.0001	0.0002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Building Age	-0.0371*	0.0223***	-0.0041**	-0.0006	-0.0067
	(0.019)	(0.006)	(0.002)	(0.007)	(0.011)
Floor	-0.0016	0.0229***	-0.0076***	0.0001	0.0006
	(0.003)	(0.008)	(0.002)	(0.003)	(0.006)
Renovation	-0.0338***	-0.1118***	0.0497***	0.0051	-0.0016
	(0.007)	(0.009)	(0.003)	(0.004)	(0.007)
Rooms	0.0475***	-0.0665***	0.0347***	0.0040	-0.0032
	(0.009)	(0.012)	(0.007)	(0.006)	(0.011)
Subway	0.0121	-0.0093	0.0133**	0.0107**	0.0057
	(0.011)	(0.007)	(0.005)	(0.005)	(0.009)
Constant	2.3416***	4.0156***	10.1538***	4.8231***	4.6709***
	(0.037)	(0.033)	(0.020)	(0.015)	(0.034)
Observations	185,187	185,187	185,187	34,417	14,173
Adjusted R^2	0.123	0.092	0.947	0.077	0.107
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes

Note: This table presents robustness checks excluding transactions involving listings that span both pre- and post- roll-out period. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table EC.12 Robustness Check on Compositional Stability of Transacted Listings

	(1) Building Size	(2) Rooms	(3) Renovation	(4) Subway
PostTreat	0.3805	-0.0070	0.0117*	-0.0031
	(0.343)	(0.006)	(0.007)	(0.003)
Constant	84.1950***	2.1884***	2.4725***	0.5331***
	(0.095)	(0.002)	(0.002)	(0.001)
Observations	193,926	193,924	193,926	193,926
Adjusted R^2	0.141	0.120	0.068	0.378
Year-Month FE	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes

Note: This table presents robustness checks on the compositional stability of transacted listings by examining whether the deployment of AI Visual systematically affects the key characteristics of transacted properties. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table EC.13 Robustness Check on Using Additional Controls: Regional-Level Economic Indicators

	(1) Log(Buyer_days)	(2) Log(Seller_days)	(3) Log(Price)	(4) Rating(buyer)	(5) Rating(seller)
PostTreat	-0.1045***	-0.2176***	0.0276***	-0.1701***	0.1804***
	(0.019)	(0.030)	(0.006)	(0.016)	(0.018)
Building Size	0.0045***	0.0057***	-0.0009***	-0.0002	0.0002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Building Age	-0.0363*	0.0237***	-0.0033*	-0.0003	-0.0056
	(0.019)	(0.007)	(0.002)	(0.006)	(0.011)
Floor	-0.0022	0.0229***	-0.0083***	-0.0012	0.0010
	(0.004)	(0.008)	(0.002)	(0.003)	(0.006)
Renovation	-0.0305***	-0.1233***	0.0495***	0.0047	-0.0034
	(0.007)	(0.009)	(0.003)	(0.004)	(0.007)
Rooms	0.0478***	-0.0671***	0.0353***	0.0066	-0.0019
	(0.009)	(0.013)	(0.007)	(0.006)	(0.010)
Subway	0.0123	-0.0073	0.0123**	0.0108**	0.0010
	(0.011)	(0.007)	(0.005)	(0.005)	(0.009)
unemployment	0.3256*	0.1398	0.0769	0.1781*	-0.0946
	(0.170)	(0.205)	(0.146)	(0.102)	(0.202)
avggdp	0.0052	-0.0205***	0.0123**	0.0008	-0.0142
	(0.010)	(0.007)	(0.005)	(0.004)	(0.020)
population	0.0001	-0.0002	-0.0001	0.0002	-0.0001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
income	0.0810	0.2875***	-0.0130	0.0730	-0.0039
	(0.156)	(0.103)	(0.088)	(0.063)	(0.197)
Constant	0.7975	1.8991*	9.8731***	3.7934***	5.1810***
	(1.406)	(1.121)	(0.917)	(0.649)	(1.599)
Observations	193,924	193,924	193,924	36,288	14,820
Adjusted R^2	0.123	0.077	0.946	0.068	0.100
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes

Note: This table presents robustness checks including additional regional-level economic controls, including district-level GDP per capita, population, disposable income per capita, and unemployment rate. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table EC.14 Robustness Check on Using Two-Way Clustered Standard Errors (District $\times$ Week)

	(1) Log(Buyer_days)	(2) Log(Seller_days)	(3) Log(Price)	(4) Rating(buyer)	(5) Rating(seller)
PostTreat	-0.1047***	-0.2176***	0.0273***	-0.1703***	0.1812***
	(0.022)	(0.030)	(0.006)	(0.016)	(0.018)
Building Size	0.0045***	0.0057***	-0.0009***	-0.0002	0.0002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Building Age	-0.0366*	0.0240***	-0.0041**	-0.0003	-0.0056
	(0.020)	(0.007)	(0.002)	(0.007)	(0.011)
Floor	-0.0021	0.0230***	-0.0082***	-0.0011	0.0010
	(0.004)	(0.008)	(0.002)	(0.002)	(0.006)
Renovation	-0.0306***	-0.1232***	0.0493***	0.0048	-0.0032
	(0.009)	(0.009)	(0.003)	(0.004)	(0.007)
Rooms	0.0476***	-0.0670***	0.0350***	0.0066	-0.0025
	(0.009)	(0.013)	(0.007)	(0.006)	(0.010)
Subway	0.0124	-0.0073	0.0131**	0.0105*	0.0007
	(0.011)	(0.007)	(0.005)	(0.005)	(0.009)
Constant	2.3368***	4.0306***	10.1461***	4.8296***	4.6732***
	(0.039)	(0.037)	(0.020)	(0.016)	(0.033)
Observations	193,924	193,924	193,924	36,288	14,820
Adjusted R^2	0.123	0.077	0.946	0.068	0.100
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes

Note: This table presents robustness checks using two-way clustered standard errors at the district and week levels. Robust standard errors, two-way clustered at the district and week levels, are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table EC.15 Robustness Check on Using City-Level Clustered Standard Errors

	(1) Log(Buyer_days)	(2) Log(Seller_days)	(3) Log(Price)	(4) Rating(buyer)	(5) Rating(seller)
PostTreat	-0.1047**	-0.2176***	0.0273**	-0.1703***	0.1812***
	(0.036)	(0.054)	(0.011)	(0.018)	(0.024)
Building Size	0.0045***	0.0057***	-0.0009***	-0.0002	0.0002
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Building Age	-0.0366	0.0240**	-0.0041*	-0.0003	-0.0056
	(0.031)	(0.009)	(0.002)	(0.006)	(0.009)
Floor	-0.0021	0.0230**	-0.0082**	-0.0011	0.0010
	(0.002)	(0.008)	(0.003)	(0.002)	(0.007)
Renovation	-0.0306***	-0.1232***	0.0493***	0.0048	-0.0032
	(0.004)	(0.021)	(0.004)	(0.005)	(0.007)
Rooms	0.0476***	-0.0670***	0.0350*	0.0066	-0.0025
	(0.008)	(0.016)	(0.017)	(0.005)	(0.007)
Subway	0.0124**	-0.0073	0.0131***	0.0105	0.0007
	(0.004)	(0.009)	(0.004)	(0.006)	(0.007)
Constant	2.3368***	4.0306***	10.1461***	4.8296***	4.6732***
	(0.056)	(0.083)	(0.039)	(0.018)	(0.034)
Observations	193,924	193,924	193,924	36,288	14,820
Adjusted R^2	0.123	0.077	0.946	0.068	0.100
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes

Note: This table presents robustness checks using standard errors clustered at the city level. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table EC.16 Robustness Check on Using Two-Way Clustered Standard Errors (City × Week)

	(1) Log(Buyer_days)	(2) Log(Seller_days)	(3) Log(Price)	(4) Rating(buyer)	(5) Rating(seller)
PostTreat	-0.1047**	-0.2176***	0.0273**	-0.1703***	0.1812***
	(0.037)	(0.054)	(0.011)	(0.018)	(0.024)
Building Size	0.0045***	0.0057***	-0.0009***	-0.0002	0.0002
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Building Age	-0.0366	0.0240**	-0.0041*	-0.0003	-0.0056
	(0.032)	(0.009)	(0.002)	(0.006)	(0.009)
Floor	-0.0021	0.0230**	-0.0082**	-0.0011	0.0010
	(0.002)	(0.008)	(0.003)	(0.001)	(0.007)
Renovation	-0.0306***	-0.1232***	0.0493***	0.0048	-0.0032
	(0.006)	(0.021)	(0.004)	(0.005)	(0.007)
Rooms	0.0476***	-0.0670***	0.0350*	0.0066	-0.0025
	(0.009)	(0.015)	(0.016)	(0.005)	(0.007)
Subway	0.0124**	-0.0073	0.0131***	0.0105	0.0007
	(0.005)	(0.009)	(0.004)	(0.006)	(0.007)
Constant	2.3368***	4.0306***	10.1461***	4.8296***	4.6732***
	(0.056)	(0.083)	(0.039)	(0.018)	(0.034)
Observations	193,924	193,924	193,924	36,288	14,820
Adjusted R^2	0.123	0.077	0.946	0.068	0.100
Year-Month FE	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes

Note: This table presents robustness checks using two-way clustered standard errors at the city and week levels. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table EC.17 Robustness Check Using Alternative DiD Estimators

	Log(Buyer_days) (1)	Log(Seller_days) (2)	Log(Price) (3)	Rating(buyer) (4)	Rating(seller) (5)
Panel A: Borusyak et al. (2024)					
Point Estimate	-0.0520***	-0.1525***	0.0204***	-0.1294***	0.2056***
Standard Error	0.0108	0.0096	0.0023	0.0146	0.0155
Lower 95% CI	-0.0730	-0.1712	0.0159	-0.1581	0.1752
Upper 95% CI	-0.0309	-0.1338	0.0248	-0.1008	0.2361
Panel B: Callaway and Sant'Anna (2021)					
Point Estimate	-0.1108***	-0.1592***	0.0435***	-0.1640***	0.2789***
Standard Error	0.0259	0.0186	0.0070	0.0160	0.0362
Lower 95% CI	-0.1616	-0.1957	0.0298	-0.1954	0.2080
Upper 95% CI	-0.0599	-0.1228	0.0571	-0.1326	0.3499

Note: This table presents robustness checks using alternative difference-in-differences estimators proposed by Borusyak et al. (2024) and Callaway and Sant'Anna (2021). *** $p < 0.01$. Point estimates, standard errors, and 95% confidence intervals are reported for alternative DiD estimators.

Table EC.18 Robustness Check: Using Alternative Dependent Variable

	(1) Sold<3Month	(2) Log(Last listed Price)
PostTreat	0.1708***	0.0191***
	(0.013)	(0.006)
Building Size	-0.0011***	-0.0009***
	(0.000)	(0.000)
Building Age	-0.0958***	-0.0012
	(0.002)	(0.002)
Floor	0.0206***	-0.0086***
	(0.002)	(0.002)
Renovation	0.0613***	0.0492***
	(0.002)	(0.003)
Rooms	0.0127**	0.0364***
	(0.005)	(0.007)
Subway	0.0061**	0.0130**
	(0.003)	(0.005)
Constant	0.3961***	10.1818***
	(0.013)	(0.020)
Observations	216,851	193,924
Adjusted R^2	0.209	0.948
Year-Month FE	Yes	Yes
Location FE	Yes	Yes

Note: This table presents robustness checks using alternative dependent variables. Matching efficiency is proxied by whether a listing is sold within three months (*Sold<3Month*) among all supply-side listings, and transaction prices are alternatively measured using the last listed price of transacted properties. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table EC.19 Selection into Review: Composition of Rated Transactions

Panel A: Buyer-side Characteristics

VARIABLES	(1) Buyer Male	(2) Buyer Age	(3) Agent Performance	(4) Agent Male
PostTreat	0.0029	-0.0091	-0.0100	0.0059
	(0.007)	(0.006)	(0.033)	(0.010)
Constant	0.5239***	0.2535***	3.5345***	0.6610***
	(0.003)	(0.002)	(0.012)	(0.004)
Observations	36,270	36,270	36,270	36,270
Adjusted R-squared	-0.002	0.017	0.531	0.441
Year-Month FE	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes

Panel B: Property Characteristics Owned by Sellers

VARIABLES	(1) Building Size	(2) Rooms	(3) Renovation	(4) Subway Access
PostTreat	0.2928	-0.0044	-0.0056	-0.0005
	(0.974)	(0.023)	(0.019)	(0.020)
Constant	85.0944***	2.1873***	2.4825***	0.5159***
	(0.421)	(0.010)	(0.008)	(0.008)
Observations	14,752	14,752	14,752	14,752
Adjusted R-squared	0.043	0.037	0.026	0.149
Year-Month FE	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes

Note: This table examines potential selection bias by testing whether the deployment of AI Visual systematically affects the observable composition of rated transactions. Specifically, it investigates whether buyer-side characteristics and seller-owned property characteristics in the review dataset change following the introduction of AI Visual. Robust standard errors are reported in parentheses.Panel A examines whether AI Visual affects the composition of buyers and the corresponding agents in charge in the review sample. Panel B examines whether AI Visual affects the composition of transacted properties owned by sellers in the review sample. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table EC.20 Predicting Time of AI Introduction

	(1) Whether_introduced
Rooms(City)	-0.0563
	(0.037)
Building Size(City)	0.0001
	(0.001)
Building Age(City)	0.0587
	(0.055)
Floor(City)	0.0178
	(0.028)
Renovation(City)	0.0087
	(0.053)
Subway(City)	0.0174
	(0.025)
Log(Price)(City)	-0.0324
	(0.029)
Log(Seller_days)(City)	0.0015
	(0.016)
Log(Buyer_days)(City)	0.0132
	(0.017)
Constant	0.8258**
	(0.284)
Observations	930
Adjusted R^2	0.949
City*Month FE	Yes

Note: This table examines whether systematic characteristics of local housing markets predict the timing of AI Visual introduction, thereby assessing the plausibility of as-if random roll-out timing. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.