AI Copilots in Real Estate

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Abstract

We study the effect of introducing AI copilot on China's largest real estate platform. The copilot provides realtors with tailored recommendations: suitable properties and response scripts for buyers, and price adjustments and property descriptions for sellers. We use a difference-in-differences design that leverages district-level variation in pre-existing mobile app penetration, given that the copilot is accessible exclusively from the app. We further validate these findings using a field experiment conducted in Jinan, a city of around 9 million residents, where AI access was randomized across neighborhoods. Our results demonstrate that the AI significantly improves market efficiency, reducing search times for buyers and listing durations for sellers, thanks to both same-side and cross-side effects. Furthermore, we find the AI's benefits are most pronounced for less-experienced agents and in thinner markets, suggesting that the technology is most effective at helping intermediaries overcome the core challenges of managing a two-sided market where high-quality matches are scarce. While transaction prices increase, we present evidence suggesting buyers are not made worse off: they report higher satisfaction and trust, their time on market decreases, and the price increase is driven by AI's buyer-facing functions, all of which are consistent with an increase in matching quality and reduced search friction rather than surplus extraction. Overall, our findings highlight AI's potential to enhance matching efficiency in complex, two-sided marketplaces by augmenting the performance of the intermediaries who facilitate transactions.

Keywords: Artificial Intelligence, Real Estate, Platforms, Two-sided Markets

1 Introduction

The rapid advancement of artificial intelligence (AI) technology has led to fast adoption across numerous sectors (Agrawal et al., 2019). AI capacities have developed from basic tasks such as writing (Noy and Zhang, 2023; Hui et al., 2024) and translation (Brynjolfsson et al., 2019; Zhu and Walker, 2024), but also moving towards more complex decision-making roles, including coding Peng et al. (2023), customer service (Luo et al., 2019; Schanke et al., 2021; Brynjolfsson et al., 2025) and risk assessment (Cong et al., 2024; Bertomeu et al., 2025).

Despite the growing empirical evidence on AI's effect, its implications for two-sided markets, such as real estate, remain underexplored. The theoretical effects of AI on these markets are ambiguous. While AI tools can improve efficiency, they may also create unintended asymmetries in information and bargaining power. By equipping one side of the market with superior data and recommendations, the AI's effect on the final distribution of surplus is unclear. A lopsided distribution could systematically disadvantage the other side, creating a risk of reduced market participation and potentially negating the overall efficiency gains. Therefore, how AI affects matching efficiency and whether it redistributes surplus between buyers and sellers remain key open questions.

In this paper, we provide novel empirical evidence on these questions by studying the introduction of an AI copilot for real estate agents on China's largest real estate platform. The AI advises agents on four key tasks: for buyers, it recommends suitable properties and reply scripts; for sellers, it suggests price adjustments and property titles and descriptions.

We leverage proprietary listing-level data from the platform covering one year before and one year after the introduction of the AI copilot. The dataset includes detailed property characteristics, pricing history, buyer and seller behaviors, and ratings and reviews from buyers and sellers of agent service. This richness allows us to document changes in equilibrium outcomes and behaviors, and also to shed light on underlying mechanisms using ratings and reviews.

Our empirical strategy exploits the exogenous introduction of AI copilot for agents on the platform. Since the copilot is exclusively accessible via the firm's mobile app, we use a difference-in-differences design based on pre-existing mobile app penetration across districts (analogous to counties in the U.S.). The identification comes from comparing outcomes between regions with high vs. low app penetration, and hence AI exposure, after the AI launch. Our specification includes rich property controls, including neighborhood fixed effects (a finer geographic unit than district) and district-by-month fixed effects. Furthermore, we analyze results from a randomized field experiment conducted in Jinna, a city with a population of around 9 million, where AI access was randomized across neighborhoods.

We find that the AI copilot significantly improves overall market efficiency and participant satisfaction. It increases the likelihood of a sale, reduces the time on market for both buyers and sellers, and leads to higher satisfaction ratings from both sides of the transaction, even as final prices increase. A decomposition of the AI's effect suggests that these improvements are driven by a combination of strong direct effects and cross-side effects. For example, tools designed to help agents with buyers also significantly reduce sellers' time on the market, and vice-versa.

We then explore the specific mechanisms driving these outcomes. On the demand side, the AI makes the search process more efficient. Buyers spend less time searching, conduct fewer on-site property viewings, and ultimately purchase homes with higher listed prices, suggesting the AI helps them find better-fitting, higher-value properties. This is supported by direct feedback from buyers, who report higher satisfaction and trust, and specifically praise the AI-enhanced agents for more optimal recommendations and more effective communication.

On the supply side, we find that agents using the AI adopt a more agile pricing strategy, characterized by more frequent but smaller price adjustments. This strategy is perceived positively by sellers, who report higher satisfaction with their agent's pricing advice and ability to market their properties effectively.

Next, we provide new evidence on AI-intermediary complementarity by showing how the AI's benefits are channeled through the agent. We find that the AI's ability to improve market outcomes, particularly its facilitation of the two-sided dynamics, is most pronounced for less-experienced agents. This suggests the technology functions as a "leveling agent" by helping novices master the core challenges of intermediating a complex market. Furthermore, we find the effectiveness of the AI is conditioned by market structure, with its benefits being larger in thinner markets where high-quality matches are inherently more difficult to find.

What happens to surpluses, given that transaction prices become higher? While higher prices and faster transactions should benefit sellers (and the platform), consumer surplus could decrease because of the higher prices, or increase if AI allows buyers to make better decisions and lowers search costs. While we cannot definitively prove this, three pieces of evidence suggest that consumers are not worse off. First, the higher buyer satisfaction and trust ratings suggest that the higher prices reflect a share of newly created value from a better match. Second, the combination of higher prices and faster sales is consistent with an outward shift in the demand curve. Third, the decomposition analysis shows the price increase is driven entirely by the AI's buyer-facing functions, while the seller-facing tools have no price effect—a finding inconsistent with a simple surplus-extraction story. Lastly, buyers seem to enjoy a more efficient search process, as evidenced by fewer on-site viewings and shorter search time. Taken together, the evidence suggests that the AI creates significant new value for buyers through improved matching quality and lower search costs, and the higher price reflects a sharing of this newly created surplus.

Overall, our findings demonstrate AI's potential to significantly enhance complex, two-sided marketplaces. The technology achieves this not just by improving efficiency for each side in isolation, but by generating powerful cross-side effects where tools designed for one side of the market create benefits for the other side. In the Chinese real estate market, this results in sellers gaining directly from faster sales and higher prices, while consumers appear at least no worse off and potentially better, due to higher-quality matches and reduced search

frictions. Our results provide practical insights for managers of two-sided platforms aiming to improve market outcomes through AI adoption.

1.1 Related Literature

Our study contributes to the growing empirical literature on the effect of AI adoption in housing markets. Previous research has primarily focused on the U.S. context, notably Zillow's pricing guidance took (Zestimate). Fu et al. (2022) study how Zestimate affects listing and selling prices, highlighting a significant feedback loop between human decisions and algorithmic recommendations. Similarly, Yu (2020) finds that sales prices depend on Zestimate values, particularly when public information is limited, thereby helping mitigate racial disparities in the housing market. Fu et al. (2023) further shows that Zestimate benefits both buyers and sellers, especially those living in poor neighborhood. Malik and Manzoor (2023) offers a model of feedback loops in ML-based pricing, showing that such loops can amplify pricing errors and lead to distorted outcomes. Taken together, these studies highlight how buyers and sellers actively incorporate AI-generated price signals into their decisions—sometimes to their benefit, but also with potential systemic risks. We extend this literature by studying a different application of AI within real estate—assisting intermediaries through AI-powered chatbots that provide pricing advice, and reduce search and communication frictions. To the best of our knowledge, this specific use of AI has not been studied, primarily due to data limitations.

Additionally, our paper contributes to the broader literature on AI adoption across various sectors. Prior studies of AI chatbots, which are in customer service settings, have found significant improvements in service outcomes, particularly for underperforming agents (Luo et al., 2019; Schanke et al., 2021; Brynjolfsson et al., 2025). Beyond chatbots, the literature has documented large AI effects on "basic" tasks such as writing, coding, and translation (Cowgill et al., 2020; Cheng et al., 2022; van Inwegen et al., 2023; Peng et al., 2023; Hui et al., 2024; Demirci et al., 2025; Brynjolfsson et al., 2018; Zhu and Walker, 2024), as well as

more creative fields including art and image generation (Zhou and Lee, 2024; Peukert et al., 2024; Goldberg and Lam, 2025) and consulting services(Dell'Acqua et al., 2023). Furthermore, AI-driven pricing and recommendation tools have proven effective in other contexts, including ridesharing platforms (Hall et al., 2015; Liu et al., 2023; Castillo, 2023), online rental markets (Zhang et al., 2021b; Pan and Wang, 2021; Huang, 2024), and e-commerce platforms (Zhang et al., 2021a; Fong et al., 2023; Shi et al., 2024). The expanding scope of AI applications presents significant opportunities and challenges across traditional and innovative sectors, including education (Mollick and Mollick, 2023), healthcare (Agrawal et al., 2024), and its integration with decentralization technologies such as blockchain (Hui and Tucker, 2023). Our work addresses a gap in this literature by providing empirical evidence from the economically significant but understudied real estate market, a gap that primarily exists due to data limitations.

2 Setting

2.1 China's Real Estate Market

Scale: The Chinese real estate market is among the largest globally, reaching total commercial housing sales of 17.36 trillion RMB in 2020.[1] Real estate is the primary form of household wealth in China, with an urban homeownership rate of 96% and residential housing assets accounting for about 69% of total household assets.[2]

Data Infrastructure: Unlike the U.S., where the Multiple Listing Service (MLS) provides industry-wide data sharing among agents, China's real estate market lacks a centralized property database. Instead, firms maintain exclusive control over their own property listings, which creates significant market fragmentation. This limits matching efficiency and market transparency, resulting in slower transactions and inefficient pricing, and potential

[1]Source: https://www.stats.gov.cn/sj/zxfb/202302/t20230203_1900967.html

[2]Source: https://m.163.com/dy/article/FB0AF3P20539ADBX.html; https://stock.hexun.com/2023-08-24/209822345.html

deadweight loss. Additionally, this data fragmentation reinforces a dense network of physical real estate stores, as consumers must rely heavily on in-person interactions with agents due to incomplete online information.

Governance Structure: Another fundamental difference is the governance structure. In the U.S., licensed brokers supervise independent agents, whereas in China, large real estate firms directly employ salaried agents who also earn commissions. This firm-based model in China frequently results in dual-agency, where agents represent both buyers and sellers, because firms want to keep transactions within the company, and agents have incentives to push their firms' listings rather than searching the entire market, which is time-consuming due to the lack of a centralized database.

Platforms: To mitigate market fragmentation and capitalize on technological advancements, innovative firms began developing integrated online-offline platforms in the late 2010s.[3] Unlike U.S. platforms (e.g., Zillow) that only aggregate listings and provide user-friendly interface, successful Chinese platforms control both data and transactions, combining MLS-style listing management, Zillow-like information dissemination, and traditional brokerage services. This vertically integrated model has allowed dominant platforms to leverage network effects, attract more buyers and sellers, and expand through acquisitions of smaller firms.

2.2 Empirical Context

We study the effect of AI copilot on the housing market in the context of one of China's largest real estate firms, which has successfully implemented platform innovation. By 2019, the firm operated roughly 8,000 offline stores in 103 cities, employing approximately 100,000 agents. In 2020, it facilitated over 2 million transactions valued at more than 2 trillion RMB, reflecting its unparalleled market reach.

[3]Around the same time, there was a broader wave of "platform revolution" in China, driven by advancements in 4G networks coverage and widespread smartphone penetration. Source: https://i.ifeng.com/c/84Ny6M6ClAZ.

The platform leverages its extensive offline network to build a centralized, authentic, and regularly updated property database. Sellers and smaller agencies are incentivized to exclusively list on this platform, creating a self-reinforcing cycle: better data improves matching quality and market outcomes, attracts more users (i.e., buyers, sellers, agents and agency companies), and deepens market penetration.[4]

The firm's mobile app was launched in 2015 during rapidly growing smartphone adoption in China. The firm's agents rely heavily on the app for client communication and service arrangements. Since its launch, the app has accumulated extensive data such as consumer preferences, agent-client interactions, and market dynamics, providing a rich foundation for developing AI tools.

All communication between buyers and sellers is mediated through agents who operate in geographically limited business areas, typically managing around 20-50 listings each. The typical transaction process on the platform is summarized in Figure A1.

Buyers initiate contact via the app or physical stores; on the app, the buyer can either browse agents in a desired area or browse listings and find the listing agents. If a buyer visits a physical store, the agent engages in a direct conversation to understand their needs. In either case, once contact is established, agents will solicit buyer preferences and then recommend suitable properties. After selecting a shortlist of properties for viewing, buyers negotiate terms directly with sellers through agent mediation. If successful, agents facilitate transaction completion.

Sellers start by contacting agents to list properties, either through the app or by visiting a physical store. After verifying the property information, agents help sellers set initial prices, upload detailed property information on the platform and write property descriptions. Agents recommend price adjustments based on current market conditions as needed. When a buyer shows interest, the agent coordinates an in-person negotiation and helps with finalizing

[4]Besides improved matching outcomes, consumers are also attracted to platform because of the strict property verification process that ensure authentic listings, as well as the high professionalism and service quality of the platform's agents.

the transaction.

2.3 Policy Change: Introduction of AI Copilot for Agents

On January 16, 2019, the firm introduced an app-exclusive AI copilot to all agents, leveraging extensive historical data. By late 2019, about 60% of AI recommendations were adopted by agents. The AI copilot gives recommendations targeted four main agent challenges. For buyers, it recommends suitable properties and reply scripts. For sellers, it suggests price adjustments and property titles and descriptions. Importantly, AI recommendations are advisory and visible only to agents, who retain full discretion over adoption decisions without managerial pressure.[5] Figure A1 illustrates how the AI copilot integrates into transaction processes.

Specifically, the AI helps agents working with buyers by leveraging transformer-based models that analyze from conversation text and browsing histories, to identify property preferences and recommend relevant listings. An example of this recommendation interface for agents is displayed in Figure 1(a). Additionally, the AI generates useful and professional reply scripts to buyer inquiries, closely matching the communication style of top-performing agents. Figure 1(b) shows an example where the buyer expressed interests in properties in highly ranked school zones, the AI recommended the agent to use a friendly, professional reply highlighting the agent's experience and expertise in the neighborhood.

For seller-focused features, the AI recommends dynamic price adjustments by analyzing historical data on comparable property listings, viewing activity, and market feedback (Figure 1(c) shows an example). It also provides appealing, optimized property title suggestions designed to attract buyers and improve conversion rates. Figure 1(d) shows an example of a recommended title: "Beautifully renovated home with 3.35-meter ceilings, high floor with great views, and all-day sunlight."

Our empirical setting offers several advantages for studying AI's effect on market out-

[5] Additionally, the company prohibits agents from requesting that buyers or sellers download and use the app, and does not allow agents to direct customers from the app to other social platforms.

comes. First, it offers a clearly-defined and exogenous shock, i.e., the unanticipated introduction of the AI copilot to all market participants on the platform. Second, the availability of granular data, including detailed property characteristics, pricing decisions, transaction outcomes, and ratings and reviews, allows us to measure market outcomes and explore underlying mechanisms. Third, the housing market has strong cross-side network effects, which allows our results to offer broader insights into how AI affects two-sided marketplaces.

3 Empirical Framework

3.1 Data

We use proprietary data from the platform. We have information on transaction details, buyer and seller behaviors, and their feedback on agents' service. This dataset covers 18 major cities in China and spans nearly two years, from late February 2018 to early January 2020. The AI copilot was deployed on the agents' working app in mid-January 2019, which is in the middle of our sample window.

First, the transaction-level dataset includes approximately 230,000 transaction records within the sample window. It contains detailed information on property characteristics (e.g., building size, age, decoration status, number of rooms, and floor level) as well as transaction details (e.g., transaction dates, prices, last listed prices, and buyers' and sellers' time on market). Additionally, each transaction record includes information on the corresponding agents, such as gender, age, tenure, and performance. We dropped around 20 records due to missing key information. In addition, we have a dataset on the supply side that records whether all listed properties within the sample window were sold within three or four months. This dataset complements the transaction dataset, which only includes properties that were eventually sold and therefore lacks information on the full distribution of days on market.[6]

[6]The number of listed properties during the sample period exceeds the number of transactions for two main reasons: first, the listings include properties that ultimately failed to sell due to factors such as unreasonable pricing; second, some properties listed toward the end of the sample window had not completed

Second, the dataset on buyer behaviors includes weekly panel data on approximately 13 million listed properties viewed by buyers on-site, as well as detailed apartment characteristics (e.g., floor level, number of rooms, building age, and size). This dataset is used to measure buyers' search behavior and demand, as on-site housing viewing is an important step in the search process before a transaction. Third, the dataset on seller behavior tracks weekly price adjustment frequency and magnitude for approximately 13 million listed properties during the sample window, along with detailed apartment characteristics. This dataset is used to quantify sellers' price adjustment behavior.

Lastly, the feedback data contains evaluations from buyers and sellers after transactions, covering approximately 90,000 entries within the sample period. This data includes overall ratings and text reviews for transaction experience. Additionally, it consists of a set of structured labels chosen by sellers and buyers to evaluate different aspects of the transaction experience: such as "accurate property recommendation", "clear on-site explanation", and "trustworthy" for buyers, and "reasonable price adjustment recommendations" and "accurate understanding of property selling points" for sellers.

In addition to these datasets, the company also provided us with pre-treatment levels of app-penetration: the proportion of transactions completed through the app at the district level, and the shares of buyers and sellers using the app at the district level.[7] Finally, we obtained district-level demographic data (i.e., population, income, GDP, and unemployment rates), from the company's internal database, which we use as additional control variables.

Table 1 presents the summary statistics for the variables used in the main outcomes. We use the natural logarithm of one plus days on market for sellers, days on market for buyers and transaction prices as our dependent variables. The mean of Log_days_seller is about 3.99, (or 55 days on market for sellers). The mean of Log_days_buyer is about 2.66, corresponding to an average time on market of about 15 days for buyers. The mean of

transactions within the observation period.

[7]In China, a district (e.g., Haidian District in Beijing) is an administrative division below the city level, with populations typically ranging from 300,000 to 2 million. It is roughly equivalent to a county in the U.S.

Log_price is 10.27, corresponding to an average transaction price of 28,800 RMB per square meter, or approximately 4,122 USD per square meter. Appendix Table A1 also presents the summary statistics for the additional variables used in the demand-side and supply-side analyses.

3.2 Empirical Strategy

Our primary objective is to examine how the adoption of AI copilot for supporting agents affects outcomes in the housing market. In our context, the AI's functionality is deeply integrated with the firm's mobile app and depends on customer-agent interactions within that channel. That is, the AI's features are designed to be used within the app's agent-client chat interface. This distinction between app-based and offline clients forms the basis of our identification strategy. Critically for our research design, the proportion of app-based versus offline clients varies significantly across geographic regions.

This geographic variation is driven by several factors. Although smartphone penetration in China's first-tier cities is nearly saturated, the share of second-hand housing transactions conducted through the app varies across regions.[8] In an interview with the company manager, we learned that the proportion of consumers using the app to contact agents ranges from about 25% to 70%, depending on several factors. First, younger buyers and sellers are more likely to communicate with agents via the app rather than visiting physical stores. Second, for high-priced properties, both buyers and sellers tend to be more cautious and prefer in-person meetings with agents over app-based interactions. Third, in areas where offline stores are sparse or less visible, a higher proportion of consumers rely on the app to connect with agents.

Our identification strategy exploits the differential proportion of users (buyers and/or sellers) using the app for transactions across districts during the pre-treatment period. We

[8] As of June 2019, 99.1% of Chinese internet users accessed the internet via smartphones.

estimate the effect using a continuous diff-in-diffs regression:

$$\mathrm{y}_{i,n,d,t} = \beta_1 \mathrm{Post}_t + \beta_2 \mathrm{Ratio}_d + \beta_3 \mathrm{Post}_t \times \mathrm{Ratio}_d + X_{i,d,t}\delta \ + \xi_n + \tau_{dt} + \epsilon_{i,n,d,t} \qquad (1)$$

Our dependent variables, $y_{i,b,d,t}$, are whether the listed property is sold within three months, the time on market for sellers, time on market for buyers, and housing transaction prices for transaction i in neighborhood (i.e., business area) n district d in year-month t. Post_t indicates whether the transaction occurred after the deployment of the AI copilot. Ratio_d indicates the proportion of housing transactions at the district level that were conducted through the app during the pre-treatment period. The specification also includes neighborhood fixed effects ξ_n to account for time-invariant neighborhood-specific confounders, district-month fixed effects to control for seasonal factors and the effect of district-specific shocks on the housing market (e.g., changes in real estate policies). $X_{i,d,t}$ represents two sets of control variables: (1) housing characteristics such as building size, number of rooms, etc., and (2) four key district-level variables—income, unemployment, GDP, population. In the robustness analyses in online appendix Table **??**, we also control for the interaction of these district-level variables with Post in the analyses.

We want to clarify the two geographic levels used in our regression analysis. The higher geographic level is the district, which is roughly equivalent to a county in the U.S. as discussed before. Within each district, there is a smaller geographic level known as a neighborhood (or "business area" in Chinese), representing localized clusters of commercial or social activities. Neighborhood boundaries are smaller in scale but may not always align perfectly within a single district.

Since our treatment group is defined based on the proportion of housing transactions conducted through the app at the district level, we control for district-level characteristics ($X_{i,d,t}$) and include district-by-month fixed effects (τ_{dt}) to capture broader geographic characteristics and time trends. The only place where we use the neighborhood level is in our

standalone location fixed effects (xi_n), which are defined at the finer, neighborhood level to account for localized neighborhood-specific attributes that may affect housing market outcomes at a more granular level.

Our coefficient of interest is β_3, which measures the effect of different levels of access to the AI copilot on key outcomes in the housing market following the deployment of the AI copilot. In our main specifications, standard errors are clustered at the district level, which is conceptually the level of random assignment (**?**). In an alternative specification, we replace Ratio_{tran} with Ratio_{buyer} and Ratio_{seller}, which represent the proportion of buyers and sellers using the app, respectively, to isolate the impact of the AI copilot's demand-side function (for buyers) and supply-side function (for sellers) on outcomes in the housing market.

The validity of our difference-in-differences design rests on three key assumptions. First, the parallel trends assumption requires that districts districts with high and low app penetration have similar time trends. While this assumption cannot be proved, we test for parallel pre-trends by estimating a flexible diff-in-diffs event-study specification:

$$\text{y}_{i,n,d,t} = \alpha\text{Period}_k + \gamma\text{Ratio}_d + \sum_{k\neq -1} \beta_k \text{ Period }_k \times \text{Ratio}_d + X_{i,d,t}\delta \ + \xi_n + \tau_{dt} + \epsilon_{i,n,d,t} \quad (2)$$

We can inspect whether the parallel trends assumption holds by checking if β_k is non-zero when k is less than 0, which corresponds to the period before the AI copilot deployment.

Second, the exclusion restriction requires that pre-existing app penetration only affects housing outcomes through its effect on AI adoption after the rollout. Our rich set of fixed effects and time-varying district-level controls account for a wide range of observable and unobservable factors. Furthermore, in our robustness checks (Appendix Table A3), we additionally control for interactions between the district-level controls and the Post dummy, and show that our main treatment effect estimates (on Post×Ratio) remain stable and statistically significant, which alleviates concerns that our findings are driven by pre-existing differential trends based on these observable characteristics.

Lastly, we need to assume the Stable Unit Treatment Value Assumption (SUTVA), which in our context assumes no spillovers from treated to untreated units. The primary concern is whether an agent, after being equipped with the AI, could indirectly benefit their offline clients (the untreated group). We consider three potential channels for such a spillover and argue that they are limited in our setting. First, an agent could attempt to directly use the AI for an offline client. We view this as impractical because the AI is not a standalone analytical tool. Its core functions are deeply integrated into the app's chat interface between the agent and a specific online client, relying on that client's data to generate real-time recommendations. Second, an agent could try to convert an offline client into an app user to enable the AI's functions. This was prevented by a strict institutional policy. During our sample period, the company explicitly prohibited agents from requesting that customers download or switch to the app for communication. Third, an agent could learn general principles from their AI-assisted interactions over time and apply this knowledge to their offline clients. While this form of learning is possible, the event study graphs (e.g., in Figures 2 and 3) show an immediate and sharp effect in the first month following the AI's introduction. The lack of a slowly ramping-up effect suggests that learning over time is not the primary driver of our results, though we cannot rule it out entirely.

Therefore, while we acknowledge these possibilities, the institutional context and the pattern of our results suggest that any such spillovers are likely limited in scope, and our estimates primarily capture the effect of the AI as intended through app-based interactions.

4 Main Results

In this section, we present the main findings of our study. We first show the overall effect of the AI copilot on key market outcomes: whether the listed property is sold within three months, time on market for sellers and buyers, transaction prices, and buyer and seller satisfaction ratings. We then decompose this effect to understand how the AI's distinct

buyer-facing and seller-facing functions contribute to these changes and generate cross-side effects.

4.1 Overall Effect

Table 2, Panel A, presents the key parameter estimates using Equation 1 (see coefficient estimates for all control variables in Appendix Table A2). Overall, results show that access to AI copilots significantly increases the likelihood that a listed property is sold within three months, decreases the time on market for both sellers and buyers, increases housing transaction prices, and increase satisfaction ratings from both buyers and sellers.

More specifically, in Column (1), we observe that for agents with average access to AI adoption (where the access rate is 0.446), the likelihood that a listed property is sold within the first three months after it is listed increases by 18.8% (0.4215*0.446) compared to the control group (agents without access to AI). Column (2) shows that for agents with average access to AI adoption, the time on market for sellers is lower by 0.198 (–0.4434*0.446) points compared to the control group. Relative to a baseline pre-treatment mean of 3.757, this represents a 5.27% decrease. In Column (3), we see that access to AI copilots reduces the time on market for buyers by 0.111 (-0.2484*0.446), or by 4.04% relative to the baseline mean of 2.747. Column (4) shows that access to AI copilots also has a positive and statistically significant effect on unit transaction prices. The estimated coefficient indicates an increase in transaction prices by 0.045 (0.10×0.446), relative to the control group, a 0.43% increase from the pre-treatment mean of 10.535.[9]

While higher transaction prices directly benefit sellers, their implications for buyer welfare is ambiguous. On one hand, if the AI primarily enhances sellers' bargaining power, the price increase could represent a simple transfer of surplus from buyers to sellers, leaving consumers worse off. On the other hand, if the AI improves matching quality by finding homes that

[9]Given that the average unit price of housing in our sample is 47,351 RMB and the average building size is 84.28 square meters, the adoption of AI copilot leads to an average increased in price by about 17,160 RMB, or about 2,400 USD (0.43% * 47,351 RMB * 84.28).

better fit buyer preferences, it can increase the total surplus created by the transaction. In this scenario, a higher price may simply reflect this added value, and buyers could still be better off, especially when also considering their reduced search costs.

Since we do not directly observe willingness-to-pay and thus cannot formally calculate changes in consumer surplus, we use buyer and seller satisfaction ratings as proxies for perceived welfare. As shown in Panel A, columns (5) and (6), we find that despite the higher prices, AI adoption leads to a significant increase in overall ratings from both buyers and sellers. Specifically, average access to the AI copilot increases ratings from buyers by 9.84% (0.2206×0.446), and ratings from sellers by 15.49% (0.3474×0.446). The increase in buyer satisfaction suggests that the benefits of improved matching quality and reduced search frictions likely outweigh the cost of the higher price.

To alleviate concerns regarding unobserved secular trends in outcomes driving the main results, in Figure 2, we present the event study results, as detailed in Equation 2. We observe an immediate and persistent effect on the six outcome variables after the adoption of AI copilots, while parallel trends are maintained during the pre-treatment period, suggesting a causal relationship between AI adoption of the outcome variables.

We also perform three additional robustness checks. First, we introduce interaction terms between four district-level covariates and *Post* to mitigate concerns over potential violations of the exclusion restriction assumption. Second, we use an alternative clustering approach by clustering standard errors at the district-week level, as opposed to the district-level clustering in our main analysis. Third, we replace the continuous *Ratio* variable with a binary indicator for treatment to verify the consistency of our results under a simplified treatment definition, to mitigate potential concerns of DiD with a continuous treatment (Callaway et al., 2024). The estimation results presented in Appendix Table A3, Table A4 and A5 remain qualitatively consistent with our baseline results in Table 2.

4.2 A Two-Sided Story

To further understand how the AI copilot functions, we decompose the AI's effect by separating its buyer-facing and seller-facing functions. We replace the single treatment intensity variable, Ratio_trans, with two more specific proxies, Ratio_buyer and Ratio_seller, and re-estimate Equation 1. The results, reported in Panel B of Table 2, show significant two-sided dynamics and cross-side effects.

First, we find that efficiency gains are a two-side effort. Column (1) shows that both buyer-focused and seller-focused tools increase the likelihood that a listed property is sold within three months after it is listed 6.77% (0.1744*0.388) and 10.91% (0.4117*0.265), respectively. More importantly, Columns (2) and (3) show that the buyer-focused tools significantly reduce the time on market for both buyers and sellers. Similarly, the seller-focused tools also significantly reduce time on market for both sellers and buyers. This shows a strong spillover effect on market efficiency: tools designed to help one side of the market create direct time-saving benefits for the other side.

Next, we find that price increases are driven by buyer-side functions. Specifically, Column (4) in Panel B shows that the increase in transaction price is driven almost entirely by AI's buyer-facing functions, shown in the coefficient on Post×Ratio_buyer. This suggests the AI's tools for buyers (e.g., better recommendations and communication) increase their willingness to pay, which in turn leads to higher final prices. In addition, the coefficient on Post×Ratio_seller is close to zero and statistically insignificant. This provides evidence against the alternative hypothesis that the AI primarily serves as a surplus-extraction tool for sellers. If the seller-facing tools were designed to enhance bargaining power, we would expect their intensive use to lead to higher prices. The null effect therefore suggests these tools are focused on improving market efficiency rather than extracting more value from buyers, reinforcing the conclusion that the price increase stems from a higher value delivered to the consumer.

Lastly, we find cross-side effects on ratings. Specifically, Columns (5) and (6) in Panel B

shows that, besides improving own-side ratings, AI's buyer-facing functions lead to significantly higher ratings from sellers, and the seller-facing functions lead to significantly higher ratings from buyers. This suggests that making the process better for one side results in a holistically better and more satisfying transaction for the other side.

To alleviate concerns regarding potential violations of the parallel trends assumption, we plot the event study estimates separately for buyer-facing and seller-facing functions in Figure 3. Overall, the graphs show parallel trends prior to the introduction of AI copilot, followed by an immediate and stable change in the outcome variables for both sets of AI functions, suggesting a causal interpretation of the estimates.

5 Mechanisms

In this section, we explore the mechanisms driving our main findings, focusing on the specific functions of the AI copilot that support agents. We show that the AI improves outcomes by enhancing the service agents provide to both sides of the market. On the demand side, the AI helps agents provide better recommendations and communication, leading to a more efficient search process for buyers. On the supply side, the AI assists with strategic pricing and property marketing, leading to more agile pricing strategies by sellers. For each side, we first examine direct participant feedback on the agent's service and then analyze the resulting changes in behavior. We end the section with a discussion on the role of two-sided market dynamics in our setting.

5.1 Demand-Side Mechanisms

Recall that the AI copilot functions as a tool for real estate agents by providing them with recommendations and prompts to help them better serve their buyer and seller clients. To this end, the AI has two primary functions designed to improve the buyer's experience: providing the agent with optimal housing recommendations tailored to their client and enhancing

agent's communication quality with AI-generated scripts[10]. We test for these mechanisms by first examining direct buyer feedback on the agent's AI-enhanced service and then analyzing the resulting changes in buyers search behavior.

Buyer Feedback on Agent's Service

We begin with the most direct evidence for our proposed mechanisms: buyers' own evaluations of the service they received from their AI-equipped agent. Table 3 shows that the AI leads to significant improvements across multiple dimensions of the buyer's experience.

First, we find that buyers perceive their agent's property recommendations as significantly more optimal. For a district with average app penetration, the likelihood that a buyer selects the "high-quality recommendation" label in the feedback system increases by a remarkable 0.176 (0.3944×0.446), or 42% relative to the pre-treatment mean (Column 1).

Second, the quality of agent-buyer communication improves substantially. This is evidenced both by a sharp decrease in buyers reporting "communication inefficiency" (Column 2) and, based on our NLP analysis of review texts,[11] a significant increase in explicit positive evaluations of the agent's communication skills (Column 3).

An important consequence of these service improvements is an increase in the buyer's trust in the agent. As shown in Column (4), the AI's introduction leads to a significant increase in the likelihood that a buyer gives their agent a "trustworthy" label in the feedback system. This finding provides strong support for the interpretation that the observed price increase stems from higher matching quality rather than surplus extraction; a process that systematically disadvantaged buyers would likely erode trust, not build it. As shown in Panel B of Table 3, all of these positive effects on the buyer experience are driven by the agent's use of the AI's buyer-facing functions.

To strengthen the causal interpretation of these findings, we conduct a series of placebo

[10]The two functions' app interface is displayed in Parts (a) and (b) of Figure 1.

[11]Guided by prior research (Niu et al., 2025), we prompt GPT-3.5 with the following instruction: "You are a business researcher. Please identify whether the following review contains a positive evaluation of the agent's communication skills. If it does, assign an indicator value of 1; otherwise, assign 0. We also cross-checked a subset of the classifications manually and found a high level of consistency with the prompt-based labels.

tests. We find that the AI has no effect on an agent's *on-site* presentation skills or perceived appearance and temperament——attributes that AI copilot is not designed to assist with. Furthermore, the AI's communication tools, which are exclusively designed for buyer-agent interactions, have no effect on ratings given by sellers. The consistently null results of these tests, which can be found in Appendix Table A6, increase our confidence that the effects we document are attributable to the AI's specific functions. The event study graphs for our main feedback results, displayed in Figure A3, are all consistent with the parallel trends assumption.

Consequences for Buyer Search Behavior

These AI-driven improvements in the agent's service quality have tangible consequences for buyer behavior. A more effective agent, equipped with better matching tools, should make their clients' search process more efficient.

Our primary measure of search effort is the number of on-site property viewings. As shown in Table 3 (Column 5), we find that the AI's buyer-facing functions lead to a significant reduction in these viewings. For a district with average buyer app penetration, AI's buyer-facing functions reduces on-site viewings by 0.138 (-0.3548×0.388), representing a 8.57% decrease from the pre-treatment mean of 1.6. To ensure this finding reflects a true increase in search efficiency per transaction, we confirm that there was no corresponding significant change in the overall market transaction volume (see Appendix Table A6).

This increased efficiency in finding the right property has a clear economic consequence: buyers transact on higher-value homes. The results in Column (6) show that the buyer-facing AI functions lead to a statistically significant increase in the last listed price of the homes that are ultimately purchased. Specifically, average access to AI copilot increases Log_listed_price by 0.043 (0.0963×0.446), a 0.41% increase from the pre-treatment mean of 10.57. This is consistent with the overall price increase documented in Section 4 and suggests that a more efficient search process helps buyers find and commit to properties that are a better, higher-value fit for their needs.

Finally, the event studies graphs for these outcomes are reported in Figure A2 in the Appendix and are consistent with the validity of the parallel trends assumption.

5.2 Supply-Side Mechanisms

We now turn to the supply-side mechanisms, where the AI copilot assists agents with two key seller-facing tasks: recommending strategic price adjustments and creating optimal property descriptions.[12] As with the demand side, we first examine direct feedback from sellers on the quality of the agent's service before analyzing the effect on their behavior.

Seller Feedback on Agent's Service

Sellers' own evaluations provide direct evidence that the AI's supply-side tools are effective. We first examine Pricing_optimal, a dummy variable equal to 1 if a seller selects the "reasonable price adjustment recommendations" label in the post-transaction feedback system. As shown in Table 4 (Column 1), the AI has a strong positive effect. For a district with average app penetration, the likelihood of a seller selecting this label increases by 0.11 (0.2465×0.446), representing a 36.7% increase relative to the pre-treatment mean.

Next, we examine Sellpoint_Accuracy, a dummy variable for when sellers select the "accurately capturing the property's key selling points." label in the feedback system. The results in Column (2) show that the AI increases the likelihood of sellers selecting this label by 14.6%. Panel B of the table confirms that both of these improvements in perceived service quality are driven specifically by the agent's use of the AI's seller-facing functions.

Consequences for Seller Pricing Strategy

These AI-driven improvements in agent advice lead to a clear and measurable shift in seller pricing strategy. We test this using two variables: Total_adjust_times, the number of price adjustments made to a property each week, and Total_adjust_mag, the magnitude of those adjustments.

The results in Table 4, Columns (3) and (4) show that agents equipped with the AI

[12] These functions' app interface are displayed in (c) and (d) of Figure 1.

advise their clients to make price adjustments more frequently, but with smaller magnitudes. Looking at the decomposed effects in Panel B, Column (3), average access to the supply-side AI function increases the weekly frequency of price adjustments by 0.032 (0.0820 $\times$ 0.388), or a 20% increase from its pre-treatment mean of 0.16. Meanwhile, this reduced the average magnitude of those adjustments by 0.308 (-0.7933 $\times$ 0.388), a 7.3% reduction from its pre-treatment (Column 4). This suggests the AI promotes a more agile pricing strategy of frequent, moderate adjustments to better align listing prices with real-time market trends, which helps avoid prolonged transaction periods. The event study graphs for outcomes in Table 4 are reported in Figure A5, which are consistent with the validity of the parallel trends assumption.

A more granular analysis, presented in Appendix Table A7, shows that the increase in adjustment frequency and magnitude is driven entirely by more frequent downward adjustments. The event study graphs for these more granular outcome variables are reported in Figure A4.

A potential concern is that changes in housing stock composition may partially drive our main supply-side results. To mitigate this concern, we conduct a supplementary analysis where we replace the dependent variable with five key property characteristics (e.g., the number of rooms and the building size) in Table Table A8, which mostly confirms that these effects are not driven by changes in the composition of listed properties.[13] Lastly, the placebo tests, shown in Columns (3) and (4) of Table A6, show that the AI has no effect on sellers' perceptions of an agent's communication skills. Since this task is not targeted by the supply-side tools by design, the insignificant effect increases our confidence that the results are attributable to the specific AI functions we study.

[13]The only exception is Column (4), where the outcome variable is the level of decoration of the property. While the estimated coefficient on Post$\times$Ratio_tran is negative, the magnitude is small and only marginally significant.

5.3 Discussion: The Role of Two-Sided Market Dynamics

The AI's impact is best understood through the lens of two-sided market dynamics. In this section, we synthesize our findings to demonstrate how the platform's tools create significant cross-side effects, and how these dynamics are moderated by both agent experience and market characteristics. We show that the AI generates reciprocal benefits for efficiency and satisfaction, and that these effects are most pronounced for less-experienced agents and in thinner markets. We did not find strong evidence on feedback loop caused by the AI copilot. Lastly, we end the section by discussing how AI has changed surplus distribution.

Reciprocal Effects on Efficiency and Satisfaction

Our main results have established that tools designed for one side of the market create powerful, positive outcomes for the other side. As shown in Table 2, Panel B, the buyer-focused AI has a significant cross-side effect on sellers, reducing their time on the market (a coefficient of -0.2376 on Post×Ratio_buyer in Column 2). Similarly, the seller-focused AI reduces buyers' time on the market (-0.2550 in Column 3). This reciprocal benefit extends to participant satisfaction: the seller-focused tools significantly improve buyer ratings (0.1528 in Column 5), and the buyer-focused tools significantly improve seller ratings (0.2926 in Column 6). A specific mechanism for this is revealed in our analysis of feedback in Table 3, Panel B, Column 1. Specifically, the estimated coefficient on Post×Ratio_seller is positive (0.2587), indicating that seller-facing tools that highlight the property's key selling points also make the AI's recommendations seem more "optimal" to buyers.

The Role of Agent Experience

The challenges of managing a two-sided market are most acute for the intermediaries who must facilitate transactions. This "cross-side skill" is something that develops with experience. How does the cross-side effects differ by agent experience? Overall, we find that the AI's ability to generate these positive cross-side effects is most pronounced for less-experienced agents, but the effect do not seem to differ by their gender or education.

More specifically, we include a triple interaction term to study how agents' tenure (rep-

resenting the number of years agents have been in the industry during the pre-treatment period) mediates the effects in Table 5. The Tenure variable has been standardized. Column 2 shows that the cross-side effects from the buyer-focused AI onto a seller's time on market is significantly larger for agents with less tenure with the platform (the triple-interaction term Post×Ratio_buyer×Tenure is positive and significant). We find similar qualitative cross-side pattern from seller-focused AI on buyer's time on market too in Column 3, although the triple interaction term is only marginally significant. This dynamic extends to ratings, as columns (5) and (6) show that the effect of buyer-focused AI on both buyer and seller ratings is also more pronounced for agents with less tenure. Note that these are not just "leveling effects" as shown in the previous literature (e.g., Brynjolfsson et al. (2025)); it suggests that the AI specifically helps less-skilled intermediaries master the core challenge of managing one side of the market in a way that benefits the other.

The findings are robust to using agent performance—an internal score used by the platform to evaluate agents calculated during the pre-treatment period— as an alternative proxy for experience (see Appendix Table A9). Lastly, we also tested for heterogeneous effects by agent gender and education but found no statistically significant differences (see Appendix Tables A10 and A11).

The Role of Market Characteristics

The effectiveness of the AI's tools is also conditioned by the market characteristics. We defined market thickness as the number of listed properties in the business area with the same number of rooms as the transacted property during the pre-treatment period, which is then normalized. In our heterogeneity analysis by market thickness (Table A12), we find that the demand-side tools are most valuable when the supply side is thin. For example, the buyer-focused AI has a larger effect on reducing sellers' time on market in areas with fewer listings (a coefficient of 0.0009 on Post×Ratio_buyer×Num_list in Column 2), and on increasing ratings from both buyers and sellers (Columns 5 and 6). This underscores that a key function of the AI is to overcome market frictions, a benefit that is most pronounced

when high-quality matches are inherently more difficult to find.

Feedback Loop?

While our evidence points to powerful cross-side effects through the agent and the AI's functions, our exploratory analysis of the direct behavioral feedback loop between buyers and sellers found little to no significant effects. Specifically, in Appendix Table A13, the outcome variable is buyers' days on market, and we interact our DiD estimator with frequency or magnitude of sellers' price adjustments. The only statistically significant triple interaction term is in column (4), and this finding suggests that the AI copilot helps sellers make more rational and effective price adjustments, thereby reducing days on market for buyers.

Implications for Surplus Distribution

A natural question that arises from our findings is what happens to consumer surplus, given that transaction prices increase. While higher prices and lower time-to-sell should benefit sellers, the effect on buyers is not immediately obvious. On the one hand, holding matching quality the same, a higher transaction price implies a lower buyer surplus. On the other hand, the use of AI may increase matching quality by allowing buyers to make better decisions and lower search costs. However, our analysis provides several pieces of evidence suggesting that buyers are not made worse off.

First, and most directly, we find a significant increase in buyers' stated satisfaction and trust following the AI's introduction (Table 3). It is unlikely that trust and satisfaction would increase if buyers felt they were being systematically disadvantaged in the transaction.

Second, the main results in Table 2 are consistent with an outward shift in the demand curve. The combination of a higher average transaction price and a shorter time on market (a proxy for increased quantity sold in a given period) suggests that overall demand has increased, which suggests that buyers are deriving more value from the properties they find.

Third, our decomposition of the price effect provides further suggestive evidence against a simple surplus-extraction story. As shown in Table 2, the price increase is driven entirely by the AI's buyer-facing functions, while the seller-facing tools—those that would be most

likely to enhance seller bargaining power—have no significant effect on price.

Lastly, buyers seem to enjoy a more efficient search process, as evidenced by fewer on-site viewings (Table 3) and shorter search time (Tables 2).

Taken together, the evidence suggests that the AI creates significant new value for buyers through improved matching quality and lower search costs, and the higher price reflects a sharing of this newly created surplus.

6 Randomized Control Trial

To provide further causal validation for our main difference-in-differences estimates, we leverage the results of a field experiment conducted by our partner firm. The experiment took place in Jinan, a second-tier city outside of our main data sample, and was designed to evaluate the effectiveness of the AI copilot tool.

The experimental design was implemented concurrently with the main AI rollout. The company randomly assigned half (34) of the 68 business areas in Jinan to a control group where the AI copilot was disabled on the agents' apps. Agents in this group were notified that the feature was temporarily unavailable for maintenance. The experiment ran for approximately 11 months through the end of 2019. As shown in Appendix Table A14, a randomization check confirms that there were no significant pre-existing differences in the main variables between the treatment and control groups, supporting the validity of the experimental design.

Table 6 presents the estimation results, which are qualitatively similar to and strongly corroborate our main findings. Compared to the control group, the deployment of the AI copilot increased the likelihood that a listed property sold within three months by 11.06%. The technology also reduced the time on market for both sellers (a 9.8% decrease) and buyers (a 19.3% decrease). Furthermore, the AI led to a 0.81% increase in final transaction prices.

While the RCT provides clean, experimental evidence, we use it as a supplementary

analysis for three reasons: the dataset for Jinan is limited to transaction-level data, the sample size is relatively small, and the design does not allow us to separately identify the effects of the AI's demand- and supply-side functions. Nonetheless, the consistency of the RCT results with our main DiD estimates provides a powerful robustness check, increasing our confidence in our primary identification strategy and the overall conclusions of the paper.

7 Conclusion

In this paper, we provide novel empirical evidence on the effect of an AI copilot introduced in a large, two-sided real estate market. Our analysis shows that the AI significantly increases overall market efficiency, reducing the time on market for both buyers and sellers. We show that these gains are driven by powerful same-side and cross-side effects, where AI tools designed to assist with one side of the transaction create tangible benefits for the other. We then show how these market-wide improvements are channeled through the intermediary, and the AI's benefits are most pronounced for less-experienced agents, suggesting the technology's key function is to help them master the core challenges of managing a two-sided market. Finally, while transaction prices increase, we present several pieces of evidence—including higher buyer satisfaction and trust, changes in market outcomes consistent with an outward shift in demand, and a decomposed price effect driven by buyer-side tools—that suggests this reflects a sharing of newly created value from a higher-quality match, rather than surplus extraction.

Our study is subject to several limitations. First, our analysis captures the effects of the AI copilot over a one-year post-period, which may not be long enough to observe longer-run equilibrium adjustments as market participants continue to adapt to the technology. Second, while we provide evidence that buyers are not made worse off, our measures of buyer welfare—such as satisfaction ratings and search costs—are indirect. A more direct quantification of consumer surplus remains a valuable avenue for future research.

Third, the institutional context of our study must be considered when assessing external validity. Our setting is the Chinese real estate market, where agents often act as two-sided intermediaries focused on making a successful match (dual agency). This differs from markets like the United States, where agents typically act as single-sided advocates for their clients. We expect our findings on improved market efficiency, reduced search costs, and the "leveling effect" to be broadly generalizable, as these address fundamental issues of reducing information friction and augmenting professional skills that exist in any market. However, our finding of a price increase may be context-specific. In general, the net price effect would be ambiguous, depending on the relative adoption and effectiveness of AI tools by competing buyer and seller agents. Consequently, the ultimate distribution of surplus in such a market—which depends on the interplay between this uncertain price effect and the gains from higher matching quality and lower search costs—remains an open question for future research.

Overall, our findings demonstrate AI's potential to enhance both matching efficiency and intermediary effectiveness in complex, two-sided marketplaces. The results provide practical insights for platforms aiming to leverage AI not just to assist individuals, but to improve the function of the market as a whole.

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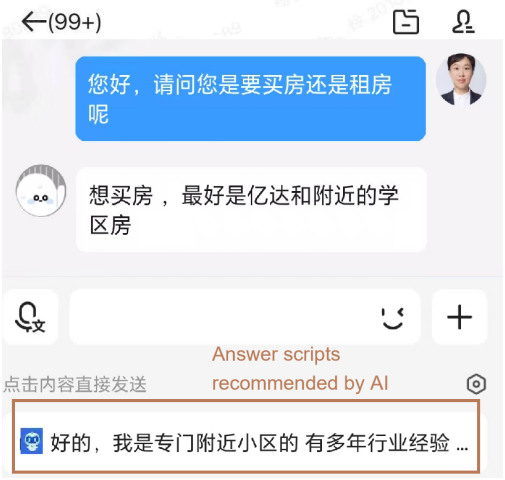
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Figures

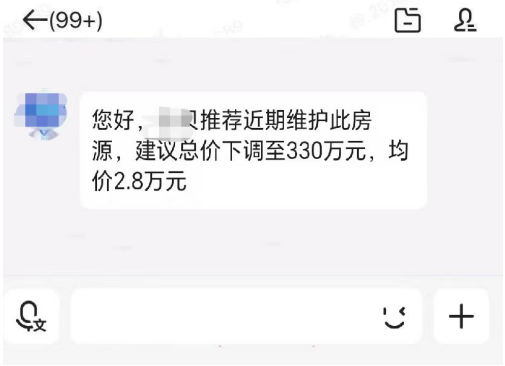
Figure 1: Sample AI Output: The App Interface for Agents



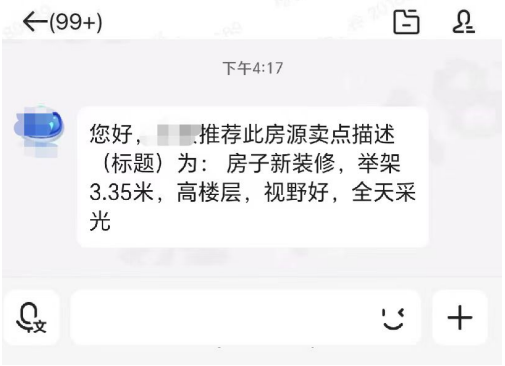
(a) AI-recommended Listings (Functioning for buyers)



(b) AI-recommended Dialogue (Functioning for buyers)



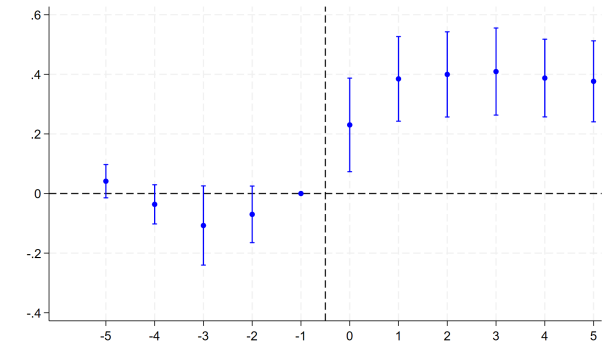
(c) AI-recommended Price adjustments (Functioning for Sellers)



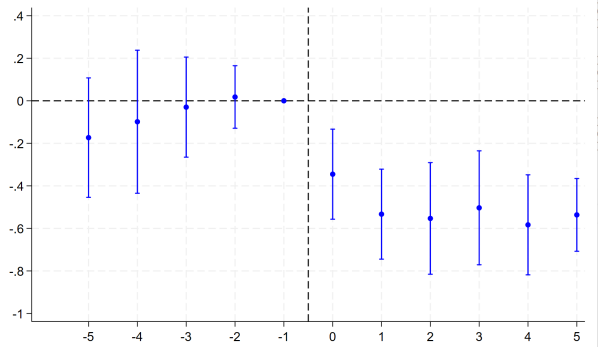
(d) AI-recommended Selling-point Descriptions (Functioning for Sellers)

Notes. This figure, as an example, displays AI-generated recommendations for agents and the corresponding app interface for agents. These recommendations are respectively targeted at buyers and sellers.

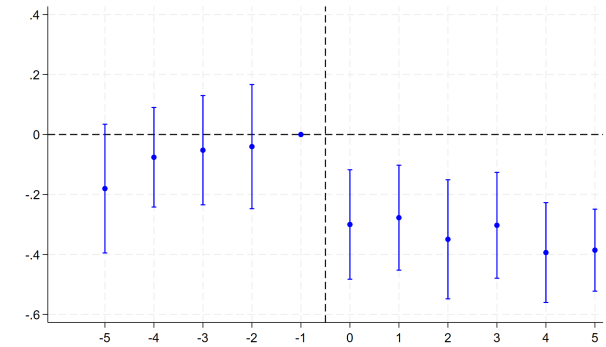
Figure 2: Event Studies for Main Outcomes: Total Effects of AI Adoption



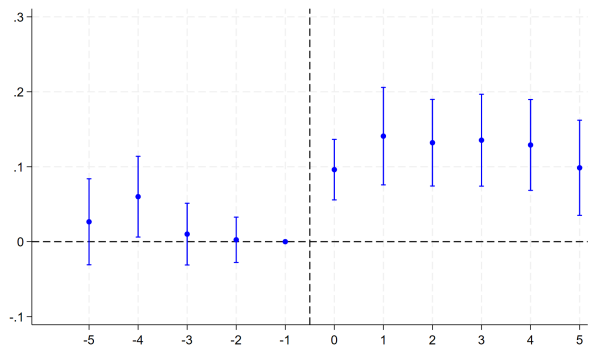
(a) Sold<3month (using Ratio_tran)



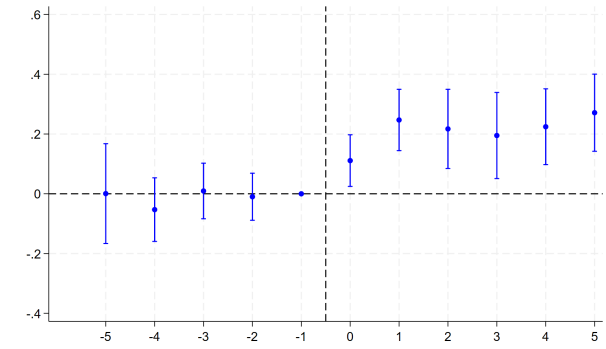
(b) Log_days_seller (using Ratio_tran)



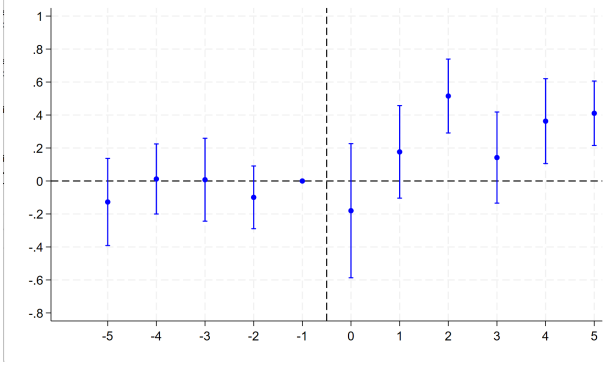
(c) Log_days_buyer (using Ratio_tran)



(d) Log_price (using Ratio_tran)



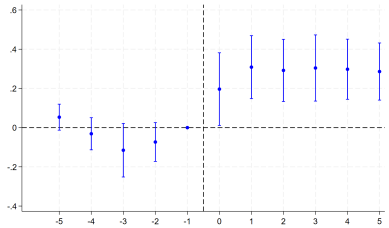
(e) Buyers' ratings (using Ratio_tran)



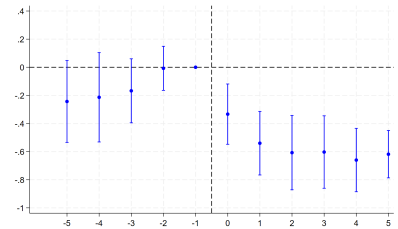
(f) Sellers' ratings (using Ratio_tran)

Notes. This figure plots the coefficients and 95% confidence intervals from event study regressions of adoption of AI on three main business outcomes: whether the listed property is sold within three months, time on market for sellers, time on market for buyers, unit transaction prices and buyers' and sellers' ratings. The specification follows Eq (1) and includes location and City×Month fixed effects. Robust standard errors are clustered at the district level.

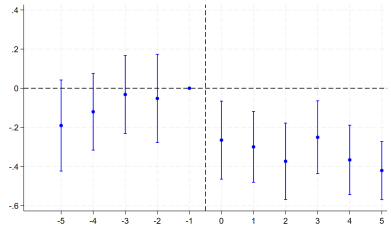
Figure 3: Event Studies for Main Outcomes: Demand-siede and Supply-side Effects of AI Adoption



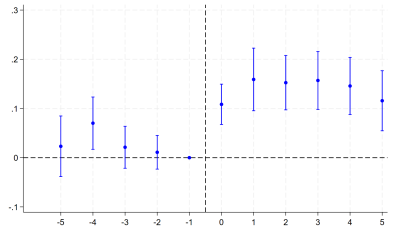
(a) Sold<3month (Ratio_buyer)



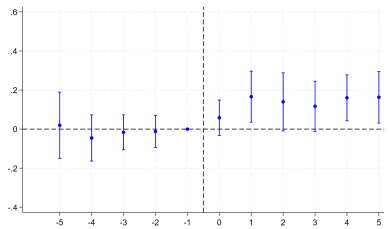
(b) Log_days_seller (Ratio_buyer)



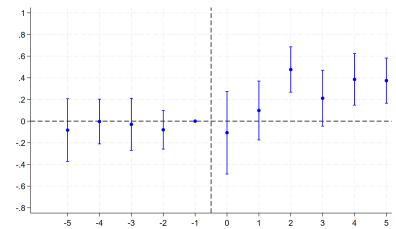
(c) Log_days_buyer (Ratio_buyer)



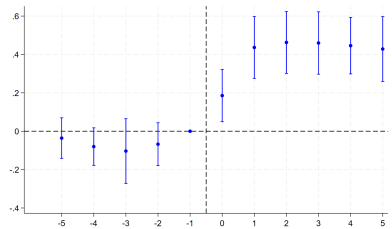
(d) Log_price (Ratio_buyer)



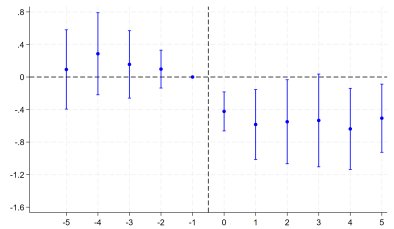
(e) Rating_buyer (Ratio_buyer)



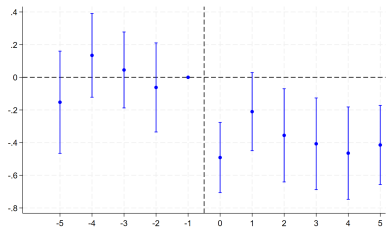
(f) Rating_seller (Ratio_buyer)



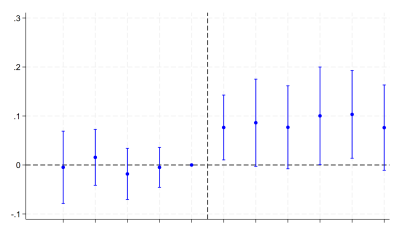
(g) Sold<3month (Ratio_seller)



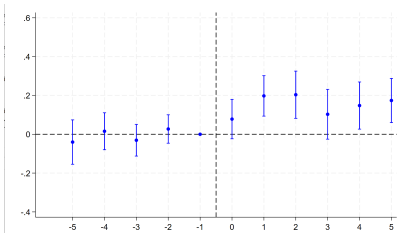
(h) Log_days_seller (Ratio_seller)



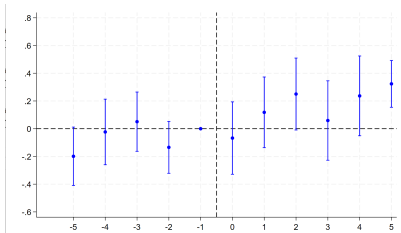
(i) Log_days_buyer (Ratio_seller)



(j) Log_price (Ratio_seller)



(k) Rating_buyer (Ratio_seller)



(l) Rating_seller (Ratio_seller)

Notes. This figure plots the coefficients and 95% confidence intervals from event study regressions of adoption of AI regarding demand-side and supply-side on three main business outcomes: whether the listed property is sold within three months, time on market for sellers, time on market for buyers, and unit transaction prices. The specification follows Eq (1) and includes location and City×Month fixed effects. Robust standard errors are clustered at the district level.

Tables

Table 1: Summary Statistics

Variable	Mean	SD	P10	Median	P90
Sold<3month	0.546	0.498	0	1	1
Log_days_seller	3.982	1.256	2.197	4.094	5.533
Log_days_buyer	2.664	1.656	0	2.639	4.905
Log_price_unit	10.274	0.763	9.326	10.267	11.275
Rating (buyer)	4.884	0.392	5	5	5
Rating (seller)	4.693	0.632	4	5	5
Log_listed_price	10.308	0.767	9.357	10.305	11.315
Discount	0.032	0.042	0	0.028	0.067
Ratio_tran	0.446	0.222	0.110	0.39	0.747
Ratio_buyer	0.388	0.208	0.117	0.353	0.716
Ratio_seller	0.265	0.162	0.085	0.276	0.444
Building size	84.28	34.178	49	80	128
Building age	3.347	1.507	1	3	5
Floor	2.118	0.801	1	2	3
Decoration	2.475	0.642	2	3	3
Room	2.183	0.794	1	2	3
School	0.478	0.5	0	0	1
Subway	0.525	0.499	0	1	1
Population	167.032	107.259	59	123	361
Unemployment	2.065	0.889	0.720	2	3.1
Gdp	12.432	7.129	5.268	9.989	19.284
Income	5.49	1.356	3.955	4.978	7.555
Education	0.092	0.288	0	0	0
Gender	0.684	0.465	0	1	1
Performance	3.43	1.36	1.130	4.02	4.71
Tenure	4.879	3.278	1	4	10

Notes. This table presents summary statistics for the main variables in the transaction dataset, which includes 231,680 data points. Among them, *building size* represents the indoor area of the property in square meters. *building age* is an indicator variable measuring the age of the building: 1 for 0-5 years, 2 for 5-10 years, 3 for 10-15 years, 4 for 15-20 years, 5 for 20-30 years, and 6 for over 30 years. $floor$ indicates the property's floor level: 0 for low, 1 for middle, and 2 for high. *decoration* is an indicator variable measuring the decoration status: 1 for un-decorated, 2 for lightly decorated, and 3 for well-decorated. *room* is an indicator variable measuring the counts of rooms in the apartment, categorized into five groups: 1 for one bedroom, 2 for two bedrooms, 3 for three bedrooms, 4 for four bedrooms, and 5 for more than four bedrooms. *school* is a dummy variable indicating proximity to a school: 1 for close, 0 otherwise. *subway* is a dummy variable indicating proximity to a subway: 1 for close, 0 otherwise. *Population* is the district's population in ten thousand people; $Income$ is the district-level per capita net income in ten thousand RMB; *Gdp* is the district's per capita GDP in ten thousand RMB; and $Unemployment$ is the district-level unemployment rate. "Rating (buyer)" and "rating (seller)" refer to the 5-point scale ratings (from 1 to 5) provided by buyers and sellers, respectively, in the user feedback system to evaluate the overall experience of the transaction. Since submitting feedback requires selecting a rating, all feedback entries include a rating value.

Table 2: The Impact of the AI Copilot on Market Outcomes and Participant Satisfaction

	(1) Sold< 3 month	(2) Log_days _seller	(3) Log_days _buyer	(4) Log_price _unit	(5) Rating (buyer)	(6) Rating (seller)
Panel A: Overall Impact of AI Copilot						
Post	-0.0372	0.5006***	0.2087***	-0.0392***	-0.0636*	-0.1947***
	(0.037)	(0.065)	(0.025)	(0.012)	(0.035)	(0.051)
Ratio_tran	-0.0602	0.0906	0.3763***	-0.0715	-0.1111**	-0.2656
	(0.060)	(0.146)	(0.104)	(0.092)	(0.047)	(0.192)
Post×Ratio_tran	0.4215***	-0.4434***	-0.2484***	0.1005***	0.2206***	0.3481***
	(0.080)	(0.145)	(0.047)	(0.029)	(0.053)	(0.061)
Panel B: Decomposed Effects and Cross-Side Spillovers						
Post	-0.0263	0.5234***	0.2202***	-0.0411***	-0.0567	-0.1897***
	(0.041)	(0.068)	(0.025)	(0.012)	(0.035)	(0.046)
Ratio_buyer	0.1221*	0.0687	0.3275***	-0.0197	-0.0424	0.0536
	(0.072)	(0.139)	(0.123)	(0.068)	(0.056)	(0.263)
Post×Ratio_buyer	0.1744*	-0.2376**	-0.1411**	0.1152***	0.1340***	0.2936***
	(0.100)	(0.107)	(0.055)	(0.028)	(0.041)	(0.056)
Ratio_seller	-0.3070***	0.2173	-0.0168	-0.1440	-0.0457	-0.1689
	(0.102)	(0.263)	(0.214)	(0.107)	(0.051)	(0.280)
Post×Ratio_seller	0.4117***	-0.4877**	-0.2550***	-0.0005	0.1525***	0.1354**
	(0.103)	(0.229)	(0.089)	(0.033)	(0.048)	(0.055)
Observations	267,882	231,680	231,680	231,680	75,596	20,336
Adjusted R^2	0.222	0.079	0.128	0.948	0.047	0.079
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City×Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table presents the results of diff-in-diff regressions estimating the impact of AI adoption. Panel A shows the overall impact. Panel B shows the impact decomposed by the AI's buyer- and seller-facing functions. All columns include location and City×Month fixed effects. Controls include apartment characteristics (e.g., building age, number of rooms, etc.) as well as unemployment, population, income, and Gdp in the respective region. The definitions of variables are provided in Table 1 and Appendix Table A1. Standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Demand-Side Mechanisms

	(1) Recomm_ optimal	(2) Talk_ inefficiency	(3) Talk_ comfort	(4) Trust	(5) Viewing	(6) Log_listed _price
Panel A: Overall Impact						
Post	-0.2835***	0.0510***	-0.0205*	-0.0278***	-0.0147	-0.0364***
	(0.049)	(0.015)	(0.012)	(0.010)	(0.085)	(0.012)
Ratio_tran	-0.1539	0.0242*	-0.0038	-0.0320	-0.1711	-0.0584
	(0.125)	(0.013)	(0.013)	(0.026)	(0.224)	(0.097)
Post×Ratio_tran	0.3944***	-0.0683***	0.0688**	0.0575**	-0.0341	0.0963***
	(0.092)	(0.024)	(0.029)	(0.023)	(0.143)	(0.029)
Panel B: Decomposed Effects						
Post	-0.2638***	0.0461***	-0.0151	-0.0266***	0.0287	-0.0384***
	(0.042)	(0.014)	(0.011)	(0.009)	(0.082)	(0.012)
Ratio_buyer	-0.3274**	0.0161	-0.0048	0.0057	0.1783	0.0067
	(0.145)	(0.011)	(0.013)	(0.029)	(0.219)	(0.068)
Post×Ratio_buyer	0.2324**	-0.0608***	0.0714***	0.0591**	-0.3548**	0.1057***
	(0.109)	(0.016)	(0.026)	(0.023)	(0.163)	(0.029)
Ratio_seller	0.2167	0.0133	-0.0051	-0.0614**	-0.6711*	-0.1752
	(0.149)	(0.013)	(0.012)	(0.026)	(0.360)	(0.110)
Post×Ratio_seller	0.2587**	-0.0129	-0.0019	0.0099	0.3094	0.0081
	(0.101)	(0.017)	(0.014)	(0.012)	(0.190)	(0.031)
Observations	75,596	75,596	75,596	75,596	13,581,455	231,680
Adjusted R^2	0.201	0.020	0.047	0.044	0.091	0.949
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City×Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table presents regression results for the demand-side mechanisms. Columns (1)-(4) show effects on buyer feedback. Column (5) shows effects on weekly on-site viewing frequency. Column (6) shows effects on the last listed prices of sold properties. All columns include location and City×Month fixed effects and standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Supply-Side Mechanisms: Assisting Agents to Improve Seller Strategy

	(1) Pricing_ optimal	(2) Sellpoint_ Accuracy	(3) Total_adjust _times	(4) Total_adjust _mag
Panel A: Overall Impact				
Post	-0.2437***	-0.1999***	-0.0103	0.1355
	(0.040)	(0.042)	(0.007)	(0.087)
Ratio_tran	-0.0598	-0.0239	-0.0362***	0.5318**
	(0.084)	(0.083)	(0.012)	(0.261)
Post×Ratio_tran	0.2465***	0.3270***	0.0639***	-0.4054**
	(0.065)	(0.087)	(0.013)	(0.155)
Panel B: Decomposed Effects				
Post	-0.2262***	-0.2003***	-0.0115	0.0516
	(0.033)	(0.028)	(0.007)	(0.097)
Ratio_buyer	0.0652	0.0672	-0.0199	-0.2197
	(0.084)	(0.094)	(0.017)	(0.263)
Post×Ratio_buyer	0.0041	0.0746	0.0204	0.2791
	(0.070)	(0.051)	(0.027)	(0.204)
Ratio_seller	-0.1749**	-0.1448	-0.0359	0.9377*
	(0.081)	(0.102)	(0.023)	(0.513)
Post×Ratio_seller	0.3331***	0.4149***	0.0820***	-0.7933***
	(0.058)	(0.053)	(0.031)	(0.244)
Observations	20,336	20,336	13,581,455	2,171,883
Adjusted R^2	0.125	0.134	0.027	0.054
Controls	Yes	Yes	Yes	Yes
City×Month FE	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes

Notes. This table presents regression results for the supply-side mechanisms. Columns (1) and (2) show effects on seller feedback labels. Columns (3) and (4) show effects on the frequency and magnitude of weekly price adjustments. All columns include location and City×Month fixed effects and standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Heterogeneity in the Effect of AI Adoption by Agents' Tenure

	(1) Sold< 3 month	(2) Log_days _seller	(3) Log_days _buyer	(4) Log_price _unit	(5) Rating (buyer)	(6) Rating (seller)
Panel A: Moderation of Overall Effect						
Post×Ratio_tran	0.518***	-0.508***	-0.315***	0.101***	0.2954***	0.5759***
	(0.082)	(0.149)	(0.052)	(0.029)	(0.060)	(0.182)
Post×Ratio_tran×Tenure	-0.0341***	0.0222***	0.0249***	-0.0002	-0.0147**	-0.0683**
	(0.003)	(0.008)	(0.007)	(0.001)	(0.007)	(0.033)
Panel B: Moderation of Decomposed Effects						
Post×Ratio_buyer	0.258**	-0.297***	-0.180***	0.117***	0.2064***	0.6272***
	(0.102)	(0.110)	(0.058)	(0.028)	(0.041)	(0.162)
Post×Ratio_buyer×Tenure	-0.0308***	0.0229**	0.0158	-0.0005	-0.0144**	-0.0838**
	(0.004)	(0.009)	(0.010)	(0.001)	(0.007)	(0.034)
Post×Ratio_seller	0.448***	-0.505**	-0.323***	0.001	0.1420***	-0.0728
	(0.105)	(0.231)	(0.093)	(0.034)	(0.043)	(0.172)
Post×Ratio_seller×Tenure	-0.0109*	0.0053	0.0247*	0.0015	0.0021	0.0309
	(0.007)	(0.009)	(0.013)	(0.002)	(0.006)	(0.037)
Observations	267,882	231,680	231,680	231,680	75,595	20,336
Adjusted	0.224	0.079	0.128	0.948	0.049	0.114
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City×Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table presents heterogeneity analysis by agent's tenure (continuous). For brevity, only the highest-order interaction terms and their constituent two-way interactions are shown. All specifications include the full set of main effects and controls as in Table 2. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6: RCT Analysis

	(1) Sold< 3 month	(2) Log_days _seller	(3) Log_days _buyer	(4) Log_price _unit	(5) Rating (buyer)	(6) Rating (seller)
Post	-0.0034	0.4739***	0.4712***	-0.1084***	-0.0689**	-0.0632
	(0.029)	(0.064)	(0.090)	(0.015)	(0.033)	(0.074)
o.Treat	-	-	-	-	-	-
Post×Treat	0.1106***	-0.3704***	-0.4506***	0.0817***	0.1247***	0.2323**
	(0.040)	(0.096)	(0.121)	(0.017)	(0.041)	(0.096)
Building size	-0.0022***	0.0074***	0.0074***	-0.0003	-0.0002	0.0020
	(0.000)	(0.001)	(0.002)	(0.000)	(0.000)	(0.001)
Building age	0.0092	-0.0152	0.0329	-0.0239***	0.0033	-0.0108
	(0.006)	(0.018)	(0.023)	(0.007)	(0.015)	(0.061)
Floor	-0.0093	0.0838***	0.0049	-0.0245***	-0.0072	0.0445
	(0.010)	(0.027)	(0.032)	(0.004)	(0.011)	(0.027)
Decoration	0.0688***	-0.1246***	0.0531	0.0369***	0.0096	0.0383
	(0.013)	(0.031)	(0.043)	(0.005)	(0.019)	(0.061)
Room	0.0193	-0.0625	-0.0877*	0.0420***	0.0227*	-0.0808
	(0.018)	(0.050)	(0.050)	(0.014)	(0.011)	(0.057)
Observations	6,748	4,031	4,031	4,031	1,378	561
Adjusted R^2	0.110	0.100	0.033	0.650	0.128	0.031
District×Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the estimation results of RCT analysis. The definitions of control variables are provided in Table 1 and Appendix Table A1. Standard errors clustered at the business area level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix A. Table and Figure

Figure A1: Flow chart

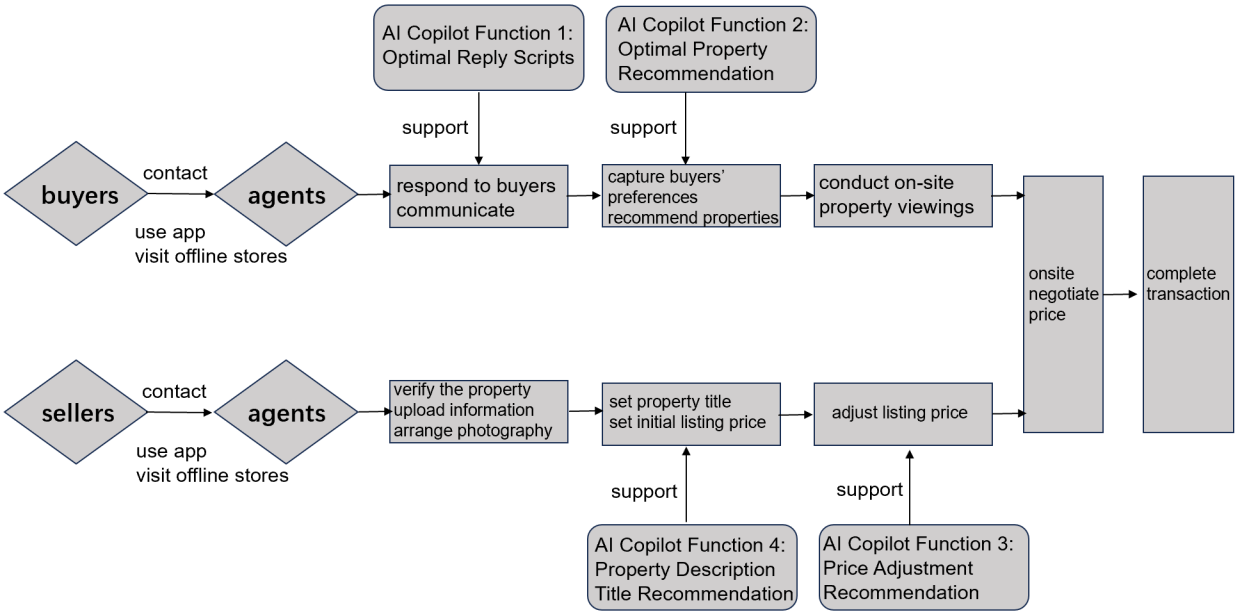


Table A2: Main Effects: Full Table [h]

	(1) Sold< 3 month	(2) Log_days _seller	(3) Log_days _buyer	(4) Log_price _unit	(5) Rating (buyer)	(6) Rating (seller)
Panel A: Overall Impact of AI Copilot						
Post	-0.0372	0.5006***	0.2087***	-0.0392***	-0.0636*	-0.1947***
	(0.037)	(0.065)	(0.025)	(0.012)	(0.035)	(0.051)
Ratio_tran	-0.0602	0.0906	0.3763***	-0.0715	-0.1111**	-0.2656
	(0.060)	(0.146)	(0.104)	(0.092)	(0.047)	(0.192)
Post×Ratio_tran	0.4215***	-0.4434***	-0.2484***	0.1005***	0.2206***	0.3481***
	(0.080)	(0.145)	(0.047)	(0.029)	(0.053)	(0.061)
Population	-0.0001	0.0002	0.0004	0.0001	-0.0000	0.0009*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment	-0.0043	-0.0709	0.1108	0.0045	-0.0166	0.1172
	(0.017)	(0.086)	(0.070)	(0.041)	(0.026)	(0.103)

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	(1) Sold< 3 month	(2) Log_days _seller	(3) Log_days _buyer	(4) Log_price _unit	(5) Rating (buyer)	(6) Rating (seller)
Gdp	-0.0023	0.0001	0.0137**	0.0144***	-0.0016	0.0157***
	(0.002)	(0.008)	(0.006)	(0.003)	(0.002)	(0.006)
Income	-0.0052	0.0109	-0.0432	0.0592**	0.0257***	-0.1233***
	(0.014)	(0.051)	(0.027)	(0.024)	(0.009)	(0.018)
Building size	-0.0014***	0.0060***	0.0044***	-0.0009***	-0.0001	0.0003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Building age	-0.1134***	0.0235***	-0.0413**	-0.0025	-0.0023	-0.0019
	(0.002)	(0.008)	(0.019)	(0.002)	(0.004)	(0.009)
Floor	0.0225***	0.0264***	-0.0043	-0.0086***	0.0015	-0.0025
	(0.003)	(0.007)	(0.003)	(0.002)	(0.002)	(0.006)
Decoration	0.0783***	-0.1307***	-0.0059	0.0511***	-0.0003	0.0124*
	(0.003)	(0.009)	(0.007)	(0.003)	(0.002)	(0.006)
Room	0.0160***	-0.0599***	0.0541***	0.0336***	0.0047*	-0.0123
	(0.005)	(0.013)	(0.008)	(0.007)	(0.003)	(0.008)
School	0.0399	-0.1612	0.1702	-0.1361**	0.0028	-0.0290*
	(0.049)	(0.176)	(0.149)	(0.065)	(0.004)	(0.016)
Subway	0.0072***	-0.0058	0.0098	0.0121**	0.0018	0.0058
	(0.002)	(0.008)	(0.010)	(0.005)	(0.003)	(0.009)
Constant	0.4951***	3.7643***	1.6696***	9.7200***	4.8407***	4.8859***
	(0.078)	(0.361)	(0.206)	(0.160)	(0.079)	(0.337)
Panel B: Decomposed Effects and Cross-Side Effects						
Post	-0.0263	0.5234***	0.2202***	-0.0411***	-0.0567	-0.1897***
	(0.041)	(0.068)	(0.025)	(0.012)	(0.035)	(0.046)
Ratio_buyer	0.1221*	0.0687	0.3275***	-0.0197	-0.0424	0.0536
	(0.072)	(0.139)	(0.123)	(0.068)	(0.056)	(0.263)
Post×Ratio_buyer	0.1744*	-0.2376**	-0.1411**	0.1152***	0.1340***	0.2936***
	(0.100)	(0.107)	(0.055)	(0.028)	(0.041)	(0.056)
Ratio_seller	-0.3070***	0.2173	-0.0168	-0.1440	-0.0457	-0.1689
	(0.102)	(0.263)	(0.214)	(0.107)	(0.051)	(0.280)
Post×Ratio_seller	0.4117***	-0.4877**	-0.2550***	-0.0005	0.1525***	0.1354**
	(0.103)	(0.229)	(0.089)	(0.033)	(0.048)	(0.055)
Population	-0.0001	0.0002	0.0004	0.0001	-0.0000	0.0009*

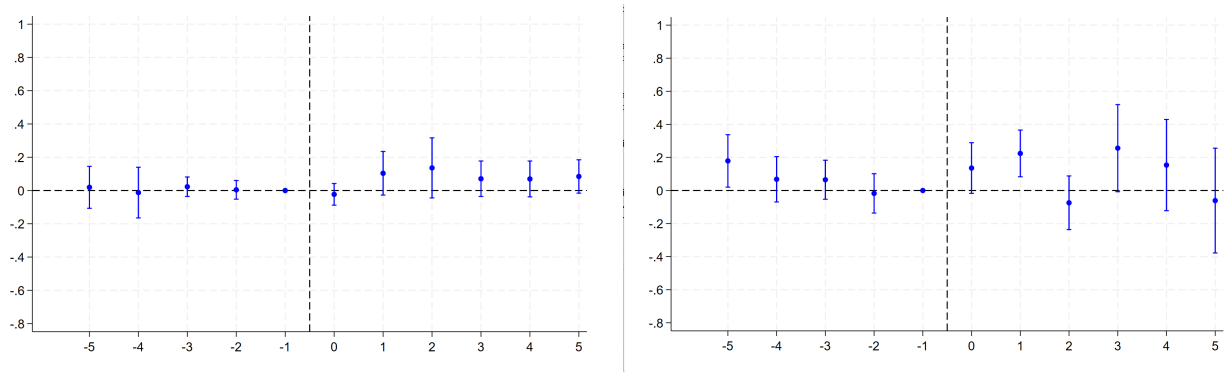
—*continued on next page*—

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	(1) Sold< 3 month	(2) Log_days _seller	(3) Log_days _buyer	(4) Log_price _unit	(5) Rating (buyer)	(6) Rating (seller)
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment	0.0040	-0.0644	0.1271*	0.0080	-0.0205	0.0972
	(0.018)	(0.087)	(0.073)	(0.041)	(0.025)	(0.125)
Gdp	-0.0025	-0.0002	0.0127**	0.0140***	-0.0015	0.0148*
	(0.002)	(0.008)	(0.006)	(0.004)	(0.002)	(0.008)
Income	-0.0048	0.0084	-0.0436	0.0585**	0.0250***	-0.1207***
	(0.014)	(0.052)	(0.027)	(0.024)	(0.009)	(0.024)
Building size	-0.0014***	0.0060***	0.0044***	-0.0009***	-0.0001	0.0003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Building age	-0.1137***	0.0234***	-0.0413**	-0.0025	-0.0023	-0.0016
	(0.002)	(0.008)	(0.019)	(0.002)	(0.004)	(0.009)
Floor	0.0224***	0.0264***	-0.0043	-0.0086***	0.0015	-0.0024
	(0.003)	(0.007)	(0.003)	(0.002)	(0.002)	(0.006)
Decoration	0.0782***	-0.1307***	-0.0058	0.0511***	-0.0003	0.0124*
	(0.003)	(0.009)	(0.007)	(0.003)	(0.002)	(0.006)
Room	0.0160***	-0.0600***	0.0541***	0.0337***	0.0046	-0.0122
	(0.005)	(0.013)	(0.008)	(0.007)	(0.003)	(0.008)
School	0.0531	-0.1188	0.1876	-0.1170*	0.0025	-0.0289*
	(0.054)	(0.173)	(0.153)	(0.068)	(0.004)	(0.016)
Subway	0.0072***	-0.0059	0.0096	0.0120**	0.0017	0.0061
	(0.002)	(0.008)	(0.010)	(0.005)	(0.003)	(0.009)
Constant	0.4778***	3.7168***	1.6820***	9.7304***	4.8288***	4.8114***
	(0.086)	(0.361)	(0.211)	(0.153)	(0.078)	(0.390)
Observations	267,882	231,680	231,680	231,680	75,596	20,336
Adjusted R^2	0.222	0.079	0.128	0.948	0.047	0.080
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City×Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table presents the full results of diff-in-diff regressions estimating the impact of AI adoption on the measures of whether the listed property is sold within three months, time on market for sellers and buyers, as well as unit transaction prices. All columns include location and City×Month fixed effects. Controls include apartment characteristics (e.g., building age, number of rooms, etc.) as well as unemployment, population, income, and Gdp in the respective region. The definitions of variables are provided in Table 1 and Appendix Table A1. Standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

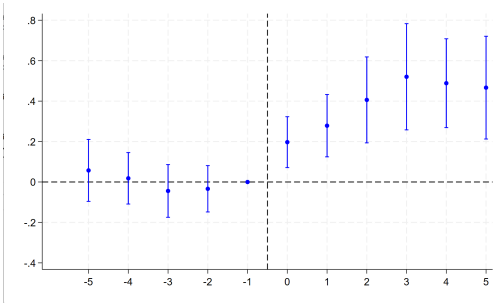
Figure A3: Event Studies for Effects on Buyers' Feedback (Placebo)



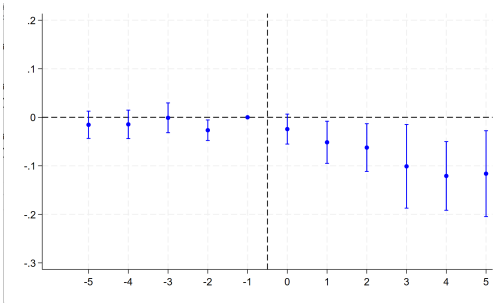
(a) Intro_well (using Ratio_tran) (b) Appearance (using Ratio_tran)

Notes. This figure plots the coefficients and 95% confidence intervals from event study regressions of adoption of AI on buyer' feedback. The specification follows Eq (1) and includes location and City×Month fixed effects. Robust standard errors are clustered at the district level.

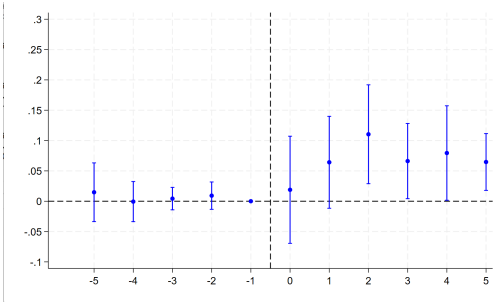
Figure A2: Event Studies for Demand-side Mechanisms



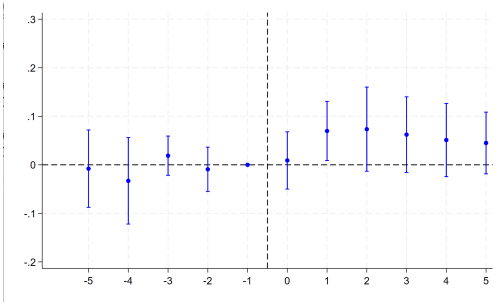
(a) recommend_optimal (using Ratio_tran)



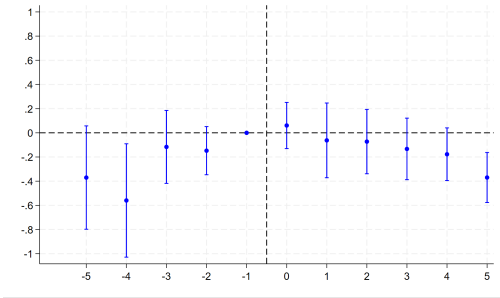
(b) Talk_inefficiency (using Ratio_tran)



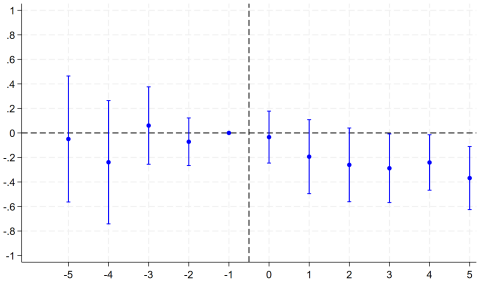
(c) Talk_comfort (using Ratio_tran)



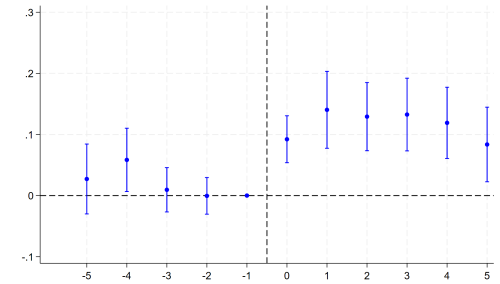
(d) Trust (using Ratio_tran)



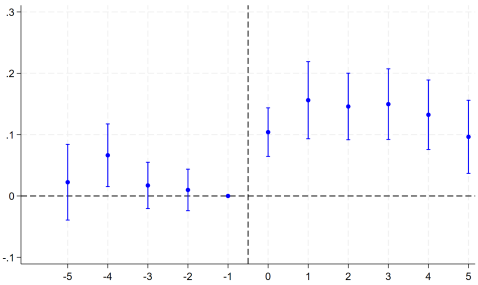
(e) Viewing (using Ratio_tran)



(f) Viewing (using Ratio_buyer)



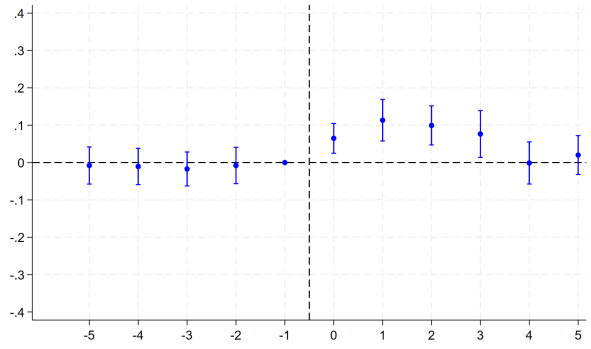
(g) Log_listed_price (using Ratio_tran)



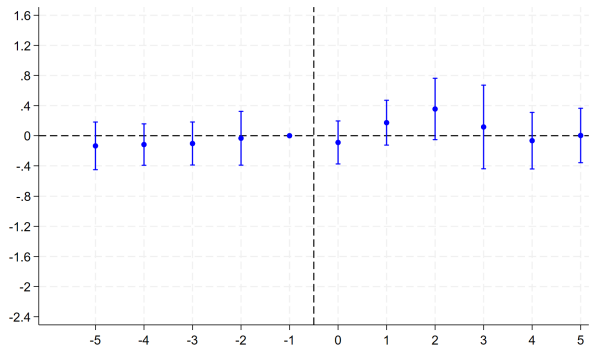
(h) Log_listed_price (using Ratio_buyer)

Notes. This figure plots the coefficients and 95% confidence intervals from event study regressions of AI adoption on various demand-side outcomes. Panels (a)-(d) show effects on buyer feedback labels. Panels (e)-(h) show effects on weekly on-site viewing frequency and the last listed prices of sold properties, presenting results for both the overall (Ratio_tran) and decomposed (Ratio_buyer) specifications. The main specification follows Eq (1) and includes location and City×Month fixed effects. Robust standard errors are clustered at the district level.

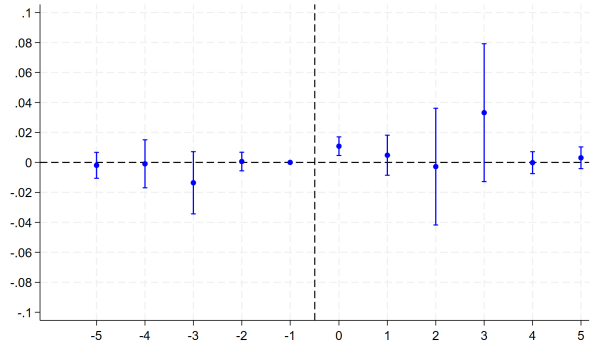
Figure A4: Event Studies for Upward and Downward Price Adjustments



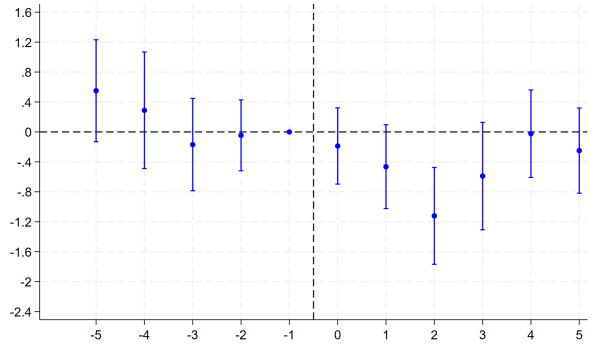
(a) Down_adjust_times (using Ratio_tran)



(b) Down_adjust_mag (using Ratio_tran)



(c) Up_adjust_times (using Ratio_tran)



(d) Up_adjust_mag (using Ratio_tran)

Notes. This figure plots the coefficients and 95% confidence intervals from event study regressions of AI adoption on Upward and Downward Price Adjustments from supply side. The main specification follows Eq (1) and includes location and City×Month fixed effects. Robust standard errors are clustered at the district level.

Table A1: Additional Summary statistics

	Mean	SD	P10	Median	P90
Demand side and supply side					
Total_adjust_times	0.187	0.533	0	0	1
Up_adjust_times	0.038	0.206	0	0	0
Down_adjust_times	0.149	0.469	0	0	1
Total_adjust_mag	4.151	3.628	1.150	3.16	8.29
Up_adjust_mag	4.75	4.684	1.120	3.33	10
Down_adjust_mag	3.96	3.325	1.090	3.09	7.8
Viewing	1.639	2.871	0	1	4
Log_volume	1.365	0.63	0.693	1.099	2.303
Num_list	233.495	228.641	42	166	495
Textual feedback (buyer)					
Recommend_optimal	0.368	0.482	0	0	1
Intro_well	0.097	0.291	0	0	0
Talk_inefficiency	0.01	0.097	0	0	0
Talk_comfort	0.012	0.108	0	0	0
Trust	0.042	0.201	0	0	0
Appearance	0.421	0.494	0	0	1
Textual feedback (seller)					
Pricing_optimal	0.255	0.436	0	0	1
Sellingpoint_accuracy	0.241	0.427	0	0	0
Talk_inefficiency	0.006	0.080	0	0	0
Talk_comfort	0.009	0.093	0	0	0
Trust	0.047	0.213	0	0	0
Appearance	0.252	0.434	0	0	1

Notes. This table presents summary statistics for the additional variables in the demand-side and supply-side datasets (which include 13,581,455 data points), as well as buyers' and sellers' evaluation data in the feedback system (which contain 75,596 and 20,336 data points, respectively).

Table A3: Robustness to Treatment Interacted with Controls

	(1) Sold< 3 month	(2) Log_days _seller	(3) Log_days _buyer	(4) Log_price _unit	(5) Rating (buyer)	(6) Rating (seller)
Panel A: Overall Impact of AI Copilot						
Post	-0.6380***	1.3622***	0.3519	-0.0917*	-0.0805	-0.3165
	(0.211)	(0.269)	(0.220)	(0.053)	(0.131)	(0.258)
Ratio_tran	0.0065	0.2368	0.4283***	-0.0858	-0.1013**	-0.2511
	(0.060)	(0.148)	(0.114)	(0.089)	(0.047)	(0.194)
Post×Ratio_tran	0.3113***	-0.6810***	-0.3340***	0.1201***	0.1906***	0.3243***
	(0.085)	(0.129)	(0.060)	(0.023)	(0.048)	(0.065)
Panel B: Decomposed Effects and Cross-Side Effects						
Post	-0.6448***	1.4293***	0.3840*	-0.0963*	0.1215***	0.2939***
	(0.204)	(0.272)	(0.217)	(0.054)	(0.039)	(0.066)
Ratio_buyer	0.1587**	0.1690	0.3635***	-0.0300	-0.0352	0.0609
	(0.076)	(0.138)	(0.129)	(0.066)	(0.057)	(0.265)
Post×Ratio_buyer	0.1209	-0.3880***	-0.1969***	0.1261***	0.1215***	0.2939***
	(0.102)	(0.076)	(0.061)	(0.024)	(0.039)	(0.066)
Ratio_seller	-0.2742***	0.2694	-0.0082	-0.1488	-0.0451	-0.1795
	(0.095)	(0.250)	(0.214)	(0.109)	(0.051)	(0.280)
Post×Ratio_seller	0.3337***	-0.5825***	-0.2745***	0.0104	0.1370***	0.1339**
	(0.093)	(0.189)	(0.087)	(0.028)	(0.049)	(0.060)
Observations	267,882	231,680	231,680	231,680	75,596	20,336
Adjusted R^2	0.229	0.081	0.128	0.948	0.049	0.081
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City×Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes. his table presents the results of difference-in-differences regressions estimating the impact of AI adoption on the main outcomes, with additional controls (i.e., the interaction term between *Post* and four regional variables). All columns include location and City×Month fixed effects. Controls include apartment characteristics (e.g., building age, number of rooms, etc.) as well as unemployment, population, income, and Gdp in the respective region, along with their interaction term with *Post*. The definitions of variables are provided in Table 1 and Appendix Table A1. Standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Robustness to Alternative Clustering

	(1) Sold< 3 month	(2) Log_days _seller	(3) Log_days _buyer	(4) Log_price _unit	(5) Rating (buyer)	(6) Rating (seller)
Panel A: Overall Impact of AI Copilot						
Post	-0.0372	0.5006***	0.2087***	-0.0392***	-0.0636*	-0.1947***
	(0.037)	(0.066)	(0.025)	(0.013)	(0.035)	(0.052)
Ratio_tran	-0.0602	0.0906	0.3763***	-0.0715	-0.1111**	-0.2656
	(0.060)	(0.141)	(0.097)	(0.092)	(0.044)	(0.208)
Post×Ratio_tran	0.4215***	-0.4434***	-0.2484***	0.1005***	0.2206***	0.3481***
	(0.080)	(0.145)	(0.046)	(0.029)	(0.053)	(0.062)
Panel B: Decomposed Effects and Cross-Side Effects						
Post	-0.0263	0.5234***	0.2202***	-0.0411***	-0.0567	-0.1897***
	(0.053)	(0.069)	(0.026)	(0.012)	(0.035)	(0.047)
Ratio_buyer	0.1221*	0.0687	0.3275***	-0.0197	-0.0424	0.0536
	(0.063)	(0.139)	(0.096)	(0.068)	(0.059)	(0.252)
Post×Ratio_buyer	0.1744*	-0.2376**	-0.1411***	0.1152***	0.1340***	0.2936***
	(0.097)	(0.108)	(0.053)	(0.029)	(0.041)	(0.057)
Ratio_seller	-0.3070***	0.2173	-0.0168	-0.1440	-0.0457	-0.1689
	(0.096)	(0.256)	(0.210)	(0.106)	(0.060)	(0.290)
Post×Ratio_seller	0.4117***	-0.4877**	-0.2550***	-0.0005	0.1525***	0.1354**
	(0.104)	(0.231)	(0.092)	(0.033)	(0.048)	(0.056)
Observations	267,882	231,680	231,680	231,680	75,596	20,336
Adjusted R^2	0.222	0.079	0.128	0.948	0.047	0.079
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City×Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table presents the results of difference-in-differences regressions estimating the impact of AI adoption on the main outcomes, with standard errors clustered at both the week and district levels. All columns include location and City×Month fixed effects. Controls include apartment characteristics (e.g., building age, number of rooms, etc.) as well as unemployment, population, income, and Gdp in the respective region. The definitions of variables are provided in Table 1 and Appendix Table A1. Standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Robustness: Using Binary Ratios

	(1) Sold< 3 month	(2) Log_days _seller	(3) Log_days _buyer	(4) Log_price _unit	(5) Rating (buyer)	(6) Rating (seller)
Panel A: Overall Impact of AI Copilot						
Post×Ratio_tran_high	0.1030*	-0.2845***	-0.1052***	0.0778***	0.1078***	0.0963***
	(0.059)	(0.087)	(0.037)	(0.015)	(0.015)	(0.027)
Post×Ratio_tran_low	-0.1365***	-0.0127	0.0712**	0.0110	-0.0167	-0.1390***
	(0.041)	(0.052)	(0.031)	(0.010)	(0.044)	(0.050)
Panel B: Decomposed Effects and Cross-Side Effects						
Post×Ratio_buyer_high	-0.0196	-0.1378	-0.0380	0.0569***	0.0338	0.1184**
	(0.052)	(0.088)	(0.058)	(0.017)	(0.023)	(0.049)
Post×Ratio_buyer_low	-0.0302	-0.0364	0.0374	0.0016	-0.0086	-0.0824
	(0.042)	(0.052)	(0.047)	(0.013)	(0.031)	(0.056)
Post×Ratio_seller_high	0.1251**	-0.1566	-0.0429	0.0215	0.0775***	0.0281
	(0.058)	(0.110)	(0.060)	(0.020)	(0.021)	(0.039)
Post×Ratio_seller_low	-0.1205**	0.0027	0.0163	0.0076	-0.0457	-0.0515
	(0.050)	(0.058)	(0.048)	(0.011)	(0.032)	(0.071)
Observations	267,882	231,680	231,680	231,680	75,596	20,336
Adjusted R^2	0.219	0.079	0.128	0.948	0.047	0.079
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City×Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table presents the results of difference-in-differences regressions estimating the impact of AI adoption on the main outcomes, with binary ratios based on quintiles. Ratio_tran_high and Ratio_tran_low are dummy variables indicating whether the value of ratio_tran falls within the top 20% or bottom 20% of the sample distribution, respectively. All columns include location and City×Month fixed effects. Controls include apartment characteristics (e.g., building age, number of rooms, etc.) as well as unemployment, population, income, and Gdp in the respective region. The definitions of variables are provided in Table 1 and Appendix Table A1. Standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Demand-Side Mechanisms: Placebo Tests and Additional Outcomes

	(1) Intro_well (Buyer)	(2) Appearance (Buyer)	(3) Talk_ineff (Seller)	(4) Talk_comfort (Seller)	(5) Trust (Seller)	(6) Discount	(7) Log_volume
Panel A: Overall Impact of AI Copilot							
Post	-0.1515***	-0.1358**	0.0139**	0.0028	0.0296**	0.0024	0.1115*
	(0.032)	(0.054)	(0.006)	(0.004)	(0.015)	(0.002)	(0.062)
Ratio_tran	-0.0527	0.0429	0.0550**	-0.0400***	0.0840***	-0.0121**	0.0421
	(0.070)	(0.129)	(0.025)	(0.015)	(0.023)	(0.005)	(0.102)
Post×Ratio_tran	0.0703	0.0408	-0.0080	-0.0026	-0.0176	-0.0033	0.1094
	(0.065)	(0.081)	(0.008)	(0.006)	(0.019)	(0.003)	(0.111)
Panel B: Decomposed Effects and Cross-Side Effects							
Post	-0.1468***	-0.1390***	0.0140***	0.0023	0.0242*	0.0023	0.1191*
	(0.029)	(0.048)	(0.005)	(0.004)	(0.014)	(0.002)	(0.065)
Ratio_buyer	0.0808	-0.1907	0.0542	-0.0553***	0.1024***	-0.0043	0.0831
	(0.081)	(0.153)	(0.036)	(0.020)	(0.030)	(0.006)	(0.110)
Post×Ratio_buyer	0.0348	0.0220	-0.0051	0.0018	0.0091	-0.0077*	-0.0010
	(0.065)	(0.063)	(0.007)	(0.006)	(0.023)	(0.004)	(0.115)
Ratio_seller	-0.2121***	0.3557**	-0.0430	0.0234	-0.0428	-0.0087	0.0677
	(0.067)	(0.151)	(0.043)	(0.019)	(0.045)	(0.009)	(0.171)
Post×Ratio_seller	0.0515	0.0455	-0.0063	-0.0050	-0.0248	0.0071	0.1660
	(0.052)	(0.052)	(0.006)	(0.006)	(0.022)	(0.005)	(0.118)
Observations	75,596	75,596	20,336	20,336	20,336	231,680	58,968
Adjusted R^2	0.168	0.207	0.017	0.049	0.120	0.089	0.612
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City×Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. This table presents results for placebo tests and additional outcomes. Columns (1)-(2) show placebo tests on buyer feedback labels not targeted by the AI. Columns (3)-(5) show placebo tests on seller feedback for communication skills. Column (6) shows the effect on on-site discounts, defined as the difference between the transaction price and last listed price, divided by the last listed price. Column (7) shows the effect on weekly transaction volume. All columns include location and City×Month fixed effects and standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A7: Supply-Side Mechanisms: Analysis of Upward and Downward Price Adjustments

	(1) Down_adjust _times	(2) Down_adjust _mag	(3) Up_adjust _times	(4) Up_adjust _mag
Panel A: Overall Impact of AI Copilot				
Post	-0.0245***	-0.0884	0.0143***	0.5693***
	(0.009)	(0.102)	(0.005)	(0.143)
Ratio_tran	-0.0301**	0.4926**	-0.0024	0.6347
	(0.013)	(0.239)	(0.005)	(0.431)
Post×Ratio_tran	0.0533***	-0.3504**	0.0106	-0.6597***
	(0.014)	(0.152)	(0.011)	(0.232)
Panel B: Decomposed Effects and Cross-Side Effects				
Post	-0.0264***	-0.1740	0.0149***	0.4694***
	(0.008)	(0.113)	(0.005)	(0.135)
Ratio_buyer	-0.0070	-0.0954	-0.0058	-0.5533*
	(0.017)	(0.273)	(0.006)	(0.322)
Post×Ratio_buyer	0.0078	0.2421	0.0126	0.0849
	(0.025)	(0.196)	(0.011)	(0.245)
Ratio_seller	-0.0512**	0.7008	0.0087	1.6021*
	(0.023)	(0.487)	(0.007)	(0.843)
Post×Ratio_seller	0.0845***	-0.6345**	-0.0026	-0.9195***
	(0.031)	(0.256)	(0.011)	(0.245)
Observations	13,581,455	1,807,297	13,581,455	491,030
Adjusted R^2	0.026	0.059	0.015	0.047
Controls	Yes	Yes	Yes	Yes
City×Month FE	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes

Notes. This table presents a detailed breakdown of price adjustment behaviors. The outcome variables are the number of downward price adjustments, the magnitude of downward price adjustments, the number of upward price adjustments, and the magnitude of upward price adjustments, respectively. Panel A shows the overall impact. Panel B shows the impact decomposed by the AI's buyer- and seller-facing functions. All columns include the full set of controls as previous tables. Standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A8: Effects on Composition of Listed Properties

	(1) Building size	**(2)** Building age	**(3)** Floor	**(4)** Decoration	**(5)** Room
Post	0.0253***	0.0093	-0.0027	0.0073**	-0.0086***
	(0.006)	(0.008)	(0.003)	(0.003)	(0.002)
Ratio_tran	-0.1961	0.2973	-0.0774***	-0.0178	0.0698
	(0.183)	(0.310)	(0.028)	(0.087)	(0.111)
Post×Ratio_tran	-0.0122	0.0189	0.0013	-0.0093*	0.0050
	(0.008)	(0.015)	(0.005)	(0.005)	(0.003)
Observations	13,581,455	13,581,455	13,581,455	13,581,455	13,581,455
Adjusted R^2	0.646	0.429	0.012	0.088	0.635
Controls	Yes	Yes	Yes	Yes	Yes
City×Month FE	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of diff-in-diff regressions estimating the impact of AI adoption on the composition of listed properties' characteristics. All columns include location and City×Month fixed effects. Controls include apartment characteristics (e.g., building age, number of rooms, etc.) as well as unemployment, population, income, and Gdp in the respective region. The definitions of variables are provided in Table 1 and Appendix Table A1. Standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A9: Heterogeneity in the Effect of AI Adoption by Agent Performance

	(1) Sold< 3 month	(2) Log_days _seller	(3) Log_days _buyer	(4) Log_price _unit	(5) Rating (buyer)	(6) Rating (seller)
Panel A: Moderation of Overall Effect						
Post×Ratio_tran	0.435***	-0.478***	-0.297***	0.103***	0.3640***	0.6465***
	(0.081)	(0.150)	(0.054)	(0.029)	(0.057)	(0.121)
Post×Ratio_tran×Performance	-0.100***	0.110***	0.0784***	-0.0018	-0.0401***	-0.1010***
	(0.009)	(0.023)	(0.027)	(0.002)	(0.015)	(0.031)
Panel B: Moderation of Decomposed Effects						
Post×Ratio_buyer	0.183*	-0.284***	-0.180***	0.116***	0.2248***	0.5409***
	(0.102)	(0.109)	(0.060)	(0.028)	(0.049)	(0.128)
Post×Ratio_buyer×Performance	-0.0849***	0.0973***	0.0627**	-0.0012	-0.0248**	-0.0830**
	(0.010)	(0.028)	(0.012)	(0.003)	(0.012)	(0.038)
Post×Ratio_seller	0.463***	-0.551**	-0.320***	-0.003	0.2388***	0.1910*
	(0.106)	(0.233)	(0.094)	(0.034)	(0.049)	(0.108)
Post×Ratio_seller×Performance	-0.0427***	0.0725**	0.0473	-0.0017	-0.0243***	-0.0219
	(0.014)	(0.031)	(0.030)	(0.004)	(0.009)	(0.032)
Observations	267,882	231,680	231,680	231,680	75,595	20,336

Notes. This table presents heterogeneity analysis by agent's pre-treatment performance score (continuous). For brevity, only the highest-order interaction terms and their constituent two-way interactions are shown. All specifications include the full set of main effects and controls as in Table 2. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A10: Heterogeneity in the Effect of AI Adoption by Agent Gender (Binary)

	(1) Sold< 3 month	(2) Log_days _seller	(3) Log_days _buyer	(4) Log_price _unit	(5) Rating (buyer)	(6) Rating (seller)
Panel A: Moderation of Overall Effect						
Post×Ratio_tran×Gender	0.0149	0.0590	-0.0392	-0.0115	-0.0192	-0.0645
	(0.030)	(0.064)	(0.071)	(0.012)	(0.042)	(0.102)
Panel B: Moderation of Decomposed Effects						
Post×Ratio_buyer×Gender	-0.0261	0.1006	-0.0053	-0.0158	-0.0391	-0.0034
	(0.060)	(0.079)	(0.083)	(0.017)	(0.034)	(0.097)
Post×Ratio_seller×Gender	0.0750	-0.0534	-0.0224	-0.0028	-0.0041	-0.0232
	(0.105)	(0.177)	(0.090)	(0.035)	(0.036)	(0.091)
Observations	267,882	231,680	231,680	231,680	75,595	20,336

Notes. This table presents heterogeneity analysis by agent gender (1 if male). All specifications include the full set of main effects, controls, and constituent lower-order interaction terms, though only the highest-order terms are displayed for brevity. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A11: Heterogeneity in the Effect of AI Adoption by Agent Education

	(1) Sold< 3 month	(2) Log_days _seller	(3) Log_days _buyer	(4) Log_price _unit	(5) Rating (buyer)	(6) Rating (seller)
Panel A: Moderation of Overall Effect						
Post×Ratio_tran×Education	-0.0312	0.1145	-0.0954	-0.0283	0.0961	-0.0535
	(0.056)	(0.094)	(0.097)	(0.019)	(0.069)	(0.160)
Panel B: Moderation of Decomposed Effects						
Post×Ratio_buyer×Education	0.0634	0.1621	-0.2051	-0.0098	0.0624	-0.1311
	(0.065)	(0.203)	(0.158)	(0.028)	(0.076)	(0.160)
Post×Ratio_seller×Education	0.0724	-0.0410	0.1368	-0.0341	0.1005	0.1334
	(0.105)	(0.337)	(0.222)	(0.037)	(0.062)	(0.135)
Observations	267,882	231,680	231,680	231,680	75,595	20,336

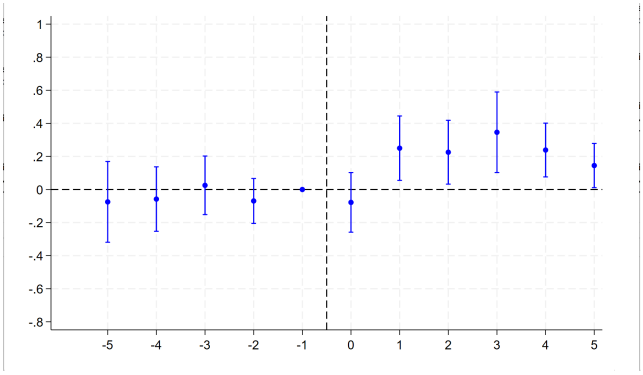
Notes. This table presents heterogeneity analysis by agent education (1 if from a prestigious university). All specifications include the full set of main effects, controls, and constituent lower-order interaction terms, though only the highest-order terms are displayed for brevity. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A12: Heterogeneity in the Effect of AI Adoption by Market Thickness

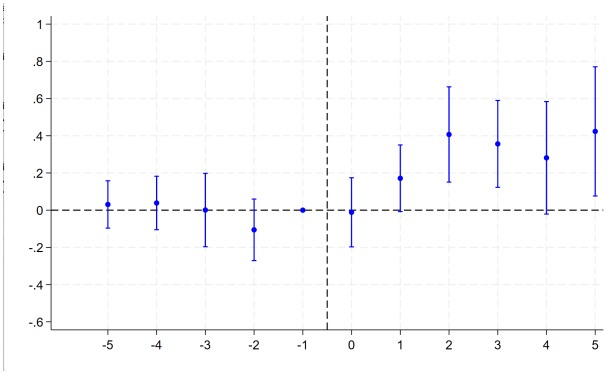
	(1) Sold< 3 month	(2) Log_days _seller	(3) Log_days _buyer	(4) Log_price _unit	(5) Rating (buyer)	(6) Rating (seller)
Panel A: Moderation of Overall Effect						
Post×Ratio_tran×Num_list	-0.0002	0.0007**	0.0003	-0.0001***	-0.0002**	-0.0007*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Moderation of Decomposed Effects						
Post×Ratio_buyer×Num_list	0.0000	0.0009***	0.0002	-0.0002***	-0.0002**	-0.0006**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Post×Ratio_seller×Num_list	-0.0002	-0.0000	0.0001	0.0001	-0.0001	-0.0001
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	267,882	231,680	231,680	231,680	75,595	20,336

Notes. This table presents heterogeneity analysis by market thickness (number of listings). For brevity, only the triple interaction terms are shown. All specifications include the full set of controls and lower-order interaction terms. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

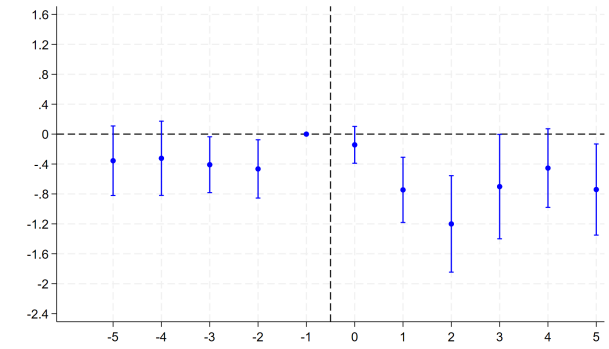
Figure A5: Event Studies for Effects on Seller Strategy



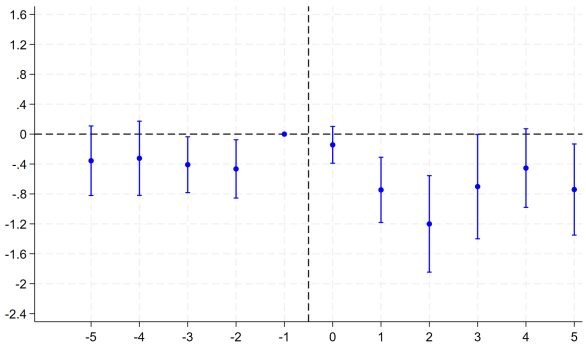
(a) Pricing_optimal (using Ratio_tran)



(b) sellingpoint_accuracy (using Ratio_tran)



(c) Total_adjust_times (using Ratio_tran)



(d) Total_adjust_mag (using Ratio_tran)

Notes. This figure plots the coefficients and 95% confidence intervals from event study regressions of the impact of adoption of AI on assisting agents to improve seller strategy. The specification follows Eq (1) and includes location and City×Month fixed effects. Robust standard errors are clustered at the district level.

Table A13: Impact of AI Copilot on Correlation between Days on Market for Buyers and Sellers' Price Adjustment Behaviors

	(1)	(2)	(3)	(4)
		Log_days_buyer		
Total_adjust_times×Post×Ratio_tran	0.0996			
	(0.936)			
Down_adjust_times×Post×Ratio_tran		0.6917		
		(1.119)		
Total_adjust_mag×Post×Ratio_tran			-0.1161	
			(0.087)	
Down_adjust_mag×Post×Ratio_tran				-0.1814**
				(0.077)
Observations	10,048	10,048	10,048	10,048
Adjusted R^2	0.291	0.293	0.292	0.291
City*Month FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Note: This table presents how AI copilot affects the correlation between district-level days on market for buyers and sellers' price adjustment behaviors. All variables are aggregated at the district level. Controls include unemployment, population, income, and Gdp in the respective district. Robust standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A14: Randomization Check

VARIABLE	Treatment Group	Control Group	p-Value of T-Test
Sold<3 month	0.5369	0.5267	0.28
Log_days_seller	3.7672	3.7777	0.43
Log_days_buyer	2.3362	2.3272	0.45
Log_price	9.8379	9.8473	0.21
Rating (buyer)	4.9261	4.9312	0.85
Rating (seller)	4.7232	4.7431	0.78
Building size	81.9303	82.0814	0.46
Building age	3.4686	3.4120	0.22
Floor	2.1543	2.1381	0.34
Decoration	2.4344	2.4463	0.35
Room	2.1380	2.1287	0.39