AI Copilots in Real Estate*

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Abstract

We study the effect of introducing an AI copilot on China's largest real estate platform in 2019. The copilot provides real estate agents with tailored recommendations: suitable properties and response scripts for buyers, and optimal price adjustments and property descriptions for sellers. Our research design leverages a difference-in-differences design exploiting district-level variation in pre-existing mobile app penetration, since the copilot is accessible exclusively from the app. The analysis includes extensive property-level controls and region-by-time fixed effects. 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 AI copilot significantly improves market efficiency by reducing buyers' search times and sellers' listing durations, with larger benefits for less experienced agents. While final transaction prices increase, we find evidence that buyers are not worse off based on their market behaviors and review texts. Sellers also improve pricing strategies and listing quality. Overall, our findings highlight AI's potential to enhance matching efficiency in the real estate market.

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

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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. Key open questions include how AI affects matching efficiency and whether it redistributes surplus between buyers and sellers in markets where intermediaries play an important role.

The theoretical effects of AI on two-sided markets are ambiguous. On the one had, AI could enhance search efficiency and outcomes form buyers, improve dynamic pricing strategies for sellers, and ultimately raise overall matching quality. On the other hand, AI recommendations may introduce inaccuracy into the system, potentially reducing matching quality. Additionally, AI might shift bargaining power and surplus asymmetrically between market sides in unanticipated ways.

In this paper, we provide novel empirical evidence on AI's effects on real estate market outcomes. Specifically, we study the introduction of an AI co-pilot for real estate agents on China's largest real estate platform in 2019. This platform is part of a major real estate firm that matches buyers and sellers and intermediates housing transactions. The AI co-pilot advises real estate agents on four key things: for buyers, it recommends suitable properties and reply scripts; for sellers, it suggests price adjustments and property titles and descriptions.

We ask two main research questions. First, how does AI affect overall market efficiency, and how does the effect differ by agent expertise? Second, does AI systematically benefit one side of the market at expensive of the other?

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 on agents. This richness allows us to document changes in equilibrium outcomes and behaviors, and also to shed light on underlying mechanisms using review texts.

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 continuous difference-in-differences approach leveraging variation in 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. To ensure robustness, we replicate the results using a coarsened treatment exposure definition to mitigate potential SUTVA violation. We also analyze results from a randomized field experiment conducted in a second-tier city (population if around 9 million) where AI access was randomized across neighborhoods.

We have three main findings. First, the introduction of AI copilot dramatically increases market efficiency: it shortens buyers' time searching for a house and sellers' time selling their properties. Final transaction price increases. These effects are more pronounced for less experienced and under-performing agents.

While higher transaction prices and faster transactions imply direct benefits to sellers (and the platform), the implications for consumer surplus, both in absolute and in relative terms, are ambiguous, as we do not observe buyers' willingness to pay (WTP). Consumer surplus could decrease because of higher prices, but it could also increase if AI allows buyers to make better decisions and lowers search costs.

To shed more light on consumer surplus effects, we study demand side behaviors. Buyers spend less time searching for homes, visit fewer properties on-site and purchase properties listed at higher prices. Faster transactions combined with higher higher price suggest an

outward shift of demand, potentially indicating increased WTP. Buyer ratings improve on average, with feedback more frequently mentioning high-quality property recommendations and efficient communication, both supporting the notion of improved consumer satisfaction.

On the supply side, sellers make more frequent, smaller downward price adjustments. Seller ratings also improve on average, with feedback more frequently mentioning reasonable price adjustment recommendations and better presentations of property selling points.

Overall, these findings suggest that AI significantly enhances matching efficiency in China's real estate market. Sellers (and the platform) gain directly, while consumers appear at least no worse off, potentially better due to better matching outcomes, and reduced search and communication frictions. Our results provide practical insights for real estate managers aiming to improve matching 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. Overall, these studies consistently show that buyers and sellers actively incorporate AI-generated price signals into their market decisions. 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 vari-

ous 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 innovative and traditional sectors, including cryptocurrency and Web3 Hui and Tucker (2023), education (Mollick and Mollick, 2023), and healthcare (Agrawal et al., 2024). 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]

[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

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 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.

[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.

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 2010, it facilitated over 2 million transactions valued at more than 2 trillion RMB, reflecting its unparalleled market reach.

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 xx 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. 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. After verifying the property infor-

[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.

mation, 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 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

[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.

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 outcomes. 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.

Second, the dataset on buyer behavior includes weekly panel data on approximately 13 million listed properties viewed by buyers on-site, as well as detailed apartment character-

istics (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 optional 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 four 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.[6] 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 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

[6]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.

analyses.

3.2 Empirical Strategy

Explain our identification strategy. - need to explain what explains the variation in smartphone penetration, and the exlucsion restriction assumption, conditional on the controls and FEs.

Our primary objective is to examine how the adoption of AI copilot for supporting agents affects outcomes in the housing market. However, since the AI copilot was deployed to all agents' apps simultaneously, it is difficult to use a staggered difference-in-difference regression framework to define treatment and control groups. Fortunately, although the AI copilot was deployed on all agents' apps at the same time, its functionality depends on whether customers use the app to reach agents. That is, for buyers and sellers who do not use the app to contact agents, the AI copilot's assistance cannot be utilized. Additionally, agents cannot disable the AI copilot's features, though whether or not to follow the AI's suggestions is up to the agents themselves.[7]

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 sell-

[7]It is worth noting that during the sample period, the company did not allow agents to request that customers download and use the app, nor did it allow agents to direct customers to other social apps for communication.

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

ers) using the app for transactions across districts during the pre-treatment period, because the AI functions can only be accessed and used on the app. The identification assumption is an exclusion restriction assumption: app penetration at the district level does not directly affect real estate market outcomes (e.g., time on market, sales price), except through its effect on AI copilot adoption. In Section 3.3, we discuss ways of testing this assumption.

3.3 Research Design

We estimate the effect of introducing AI copilot on market outcomes 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 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 xx, 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.

A key assumption of the diff-in-diffs design is that groups with high access to the AI copilot experience similar trends in housing transactions and the behavior of buyers and sellers before the deployment of the AI copilot (i.e., maintaining parallel trends). To test this assumption, we estimate a flexible diff-in-diffs event-study specification as follows:

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

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.

4 Main Results

4.1 Overall Impact

Table 2 examines how the adoption of AI copilots for supporting agents affects three main outcomes in the housing market, as estimated using Equation (1): time on market for sellers and buyers, and transaction prices.[9] In Columns (1)-(3), we show that access to AI copilots significantly decreases the time on market for both sellers and buyers, and increases housing transaction prices. Specifically, Column (1) shows that, for agents with average access to AI adoption (where the access rate is 0.446), the time on market for sellers was lower by 0.248 (-0.5569×0.446) points compared to the control group (agents without access to AI). Relative to a baseline pre-treatment mean of 3.742, this represents a decrease of 6.62%. In Column (2), we see that access to AI copilots reduces the time on market for buyers by 0.137 (-0.3073×0.446), compared to a baseline mean of 2.747. Column (3) shows that access to AI copilots also has a positive and statistically significant impact on transaction prices. The estimated coefficient indicates an increase in transaction prices by 0.137 (0.12×0.446), relative to the control group, a 1.3% increase from the pre-treatment mean of 10.534.[10] Figure 2 presents the corresponding event studies for the above three outcomes. In Figure 2, we observe an immediate and significant impact on time on market for both sellers and buyers, as well as on transaction prices, following the adoption of AI copilots, while parallel trends are maintained during the pre-treatment period. Taken together, the adoption of AI copilots for supporting agents improves the matching efficiency in the housing market (as measured by reduced time on market) and has an unintended positive impact on transaction prices, which in turn benefit for sellers.

To further understand how the AI copilot functions , we introduce Ratio_buyer and

[9]The full table with the coefficients for control variables is reported in Table A2

[10]Considering that the average unit price of housing in the sample is 47,351 RMB and the average building size is 84.28 square meters, the adoption of AI copilot leads to a significant wealth redistribution of about 51,880 RMB, or approximately 7,411 USD (1.3% * 47,351 RMB * 84.28). This is equivalent to 1.69 times the per capita disposable income of Chinese residents in 2019.

Ratio_seller, which represent the proportion of buyers and sellers who complete transactions using the app, respectively, to quantify and isolate the effects of the AI copilot's demand-side function (for buyers) and supply-side function (for sellers). We include their interaction terms with *Post* and re-estimate Eq (1). The estimation results in Columns (4)-(6) illustrate the impacts of AI copilot on the demand side and the supply side, respectively, for the three key outcomes. In Column (4), we can see that both the estimates on Post×Ratio_buyer and Post×Ratio_seller are negative and statistically significant, suggesting that AI copilot's functionality for both buyers and sellers can effectively reduce time on market for sellers. In terms of magnitudes, average access to the demand-side function of AI copilot reduces time on market for sellers by 0.109 (-0.2815×0.388), a 2.91% decrease from the pre-treatment mean of 3.742. Similarly, average access to the supply-side AI copilot also reduces time on market for sellers by 0.135 (-0.5101×0.265). In Column (5), we find that both the demand-side and supply-side functionality of the AI copilot reduce time on market for buyers. Column (6) shows that the AI copilot's demand-side functionality significantly increases transaction prices, while its supply-side functionality does not have a significant effect on transaction prices. This can be because the AI copilot only increases buyers' willingness to pay when it directly serves them by offering better services, which in turn positively impacts transaction prices. In Figure 3, we present the corresponding event study estimates. We observe that the event studies satisfy the parallel trends assumption prior to the adoption of AI copilot, followed by an immediate and stable increase in Parts (a) through (e) (except part (f), since it is insignificant in our results).

We also conduct two robustness checks: one using alternative clustering for standard errors at the district and week two-way level, and another by replacing the continuous *Ratio* with a binary variable to represent treatment groups. The estimation results presented in Appendix Table A3 and A4 remain qualitatively consistent with our baseline results in Table 2.

4.2 Heterogeneity

In this section, we explore a series of heterogeneity to further understand how AI copilots assist agents in improving matching efficiency in the housing market. The heterogeneous analyses include four key agent characteristics: performance, tenure, gender, and education, as well as market thickness on the supply side.

4.2.1 Heterogeneity by Agents' Performance and Tenure

We first investigate whether low-performance agents benefit more from the AI copilot's support. The rationale is that low-performance agents generally provide low-quality service to buyers and sellers—for example, they may struggle to make optimal recommendations for buyers—so they rely more on AI copilots to support their decision-making. In contrast, high-performance agents are able to make relatively optimized recommendations and provide better service to customers, so the AI copilot can have less supports for them. To explore the heterogeneity in agents' performance, we introduce a new variable, $Performance$, which represents the agents' performance score during the pre-treatment period, and interact it with our main independent variable Post×Ratio_tran.

The estimation results are presented in Table 3. In Columns (1)-(2), we find that the coefficients on Post×Ratio_seller×Performance are positive and statistically significant, indicating that the impacts of the AI copilot on time on market for buyers and sellers are weaker among higher-performance agents. In terms of magnitudes, in Column (1), we see that following the adoption of AI copilot, a 1 standard deviation reduction in $Performance$ (moving to lower pre-treatment performance agents) is associated with an additional decrease in time on market for sellers by 0.15 (0.1115×1.36). Similarly, in Column (2), a 1 standard deviation reduction in $Performance$ is associated with an additional decrease in time on market for buyers by 0.10 (0.0764×1.36). In Column (3), we observe that while the coefficient on Post×Ratio_seller×Performance is negative, it is insignificant, indicating that low-performance agents do not obtain significantly greater benefits in transaction prices

compared to high-performance agents. In Columns (4) through (6), we present estimation results on the split effects of AI functionality on the supply and demand sides, finding results similar to those in Columns (1) through (3). In Column (4), we observe that low-performance agents benefit more from AI copilots on both the supply and demand sides, in terms of reducing time on market for sellers. In Column (5), we show that low-performance agents benefit more from the AI copilot's demand-side function in reducing time on market for buyers. Then, we also replace the continuous variable $Performance$ with a binary variable, $Rerf_dum$, which takes a value of 1 if $Performance$ is above the sample median, and 0 otherwise. The estimation results reported in Table A5 remain consistent with the results in Table 3.

Next, we explore whether the impact of the AI copilot on the three main housing market outcomes varies based on agents' tenure. Our logic is that less-experienced agents tend to have weaker skills in interacting with customers and recommending properties, so they obtain greater benefits from the AI copilot compared to more experienced agents. To examine the heterogeneity based on agents' tenure, we include a variable $Tenure$ (representing the number of years agents have been in the industry during the pre-treatment period) and its interaction term with Post×Ratio.

The heterogeneity results are presented in Table 4. In Column (1), we find that the negative impact of the AI copilot on time on market for sellers is weaker for more experienced agents. The magnitude of the estimate shows that following the adoption of AI copilot, a 1 standard deviation reduction in $Tenure$ is associated with an additional decrease in time on market for sellers by 0.075 (0.0229×3.278). In Column (2), we similarly find that the negative impact of the AI copilot on time on market for buyers is weaker for more experienced agents, with the magnitude indicating that a 1 standard deviation reduction in $Tenure$ is associated with an additional decrease in time on market for buyers by 0.08 (0.0245×3.278). Column (3) shows that there is no significant difference in the impact of AI copilot on transaction prices between high- and low-tenure agents. In Columns (4) through (6), we further split the AI

copilot's impact on the demand-side and supply-side functions, and find similar results as in Columns (1) through (3). We also replace *Tenure* with a binary variable Tenure_dum, which takes a value of 1 if *Tenure* is above the sample median, and 0 otherwise. The estimation results presented in Table A6 remain qualitatively consistent with those in Table 4.

In sum, the estimation results on performance and tenure heterogeneity suggest that low-performance and less-experienced agents benefit more from the AI copilot, which may help narrow the performance and tenure gaps between agents.

4.2.2 Heterogeneity by Agents' other Characteristics

Then, we explore the heterogeneous effects of AI copilot adoption based on agents' gender and education. This dimension of heterogeneity is important for understanding the impact of AI on labor market inequality. On one hand, previous studies suggest that AI may exacerbate productivity inequality, as workers with higher education and males may be better at utilizing AI functionalities. On the other hand, workers with lower education and females may have lower productivity and skills, meaning they can benefit more from the deployment of AI assistants.

To test this heterogeneity, we introduce *Gender* (which takes a value of 1 if the agent is male and 0 if female) and *Education* (which takes a value of 1 if the agent graduated from a prestigious university, otherwise 0) and their interaction terms with Post×Ratio. The estimation results are presented in Table A7 and Table A8, respectively. In Columns (1) through (6) of both tables, we find that all coefficients on the triple interaction terms are statistically insignificant, indicating that there are no significant differences in the benefits from the AI copilot between male and female agents or between high-education and low-education agents. This may be because, in the context of real estate agency, there are no substantial performance differences between male and female agents or agents with different education levels. Additionally, the use of AI copilot is simple, and thus, gender or education level do not significantly affects an agent's ability to use AI copilot.

4.2.3 Heterogeneity by Market Thickness

Finally, we consider how our main effects vary in areas with different levels of market thickness on the supply side (i.e., the number of listed properties). This component of heterogeneity is important in the housing market context and helps us understand how the AI copilot functions. On one hand, a higher market thickness in the business area of a transaction may indicate that the agent's daily workload is larger, thereby leading to greater productivity benefits from the deployment of AI copilot. On the other hand, areas with higher market thickness may provide agents with a larger selection of properties, making it easier to satisfy the buyer's requirements (i.e., having a larger consideration set to meet the buyer's demand threshold), thereby leading less benefits from the deployment of AI copilot.

To examine this dimension of heterogeneity, we introduce a new variable, Num_list (which represents the number of listed properties in the business area with the same number of rooms as the transacted property during the pre-treatment period), and its interaction term with Post×Ratio. The estimation results are presented in Table A9. Across Columns (1) through (6), we find that the coefficients on Post×Ratio×Num_list are all statistically insignificant, indicating that the impact of AI copilot is homogeneous across areas with different levels of market thickness. This may be because the AI function amplifying effect caused by the higher workload in high-market-thickness areas, is offset by the AI function weakening effect in the recommendation decision-making process.

4.3 Supplementary RCT Analysis

At the same time as deploying the AI copilot, our data firm also conducted a copilot RCT experiment in a second-tier city-Jinan (outside of our data sample) to assess the AI tool's effectiveness and inform future development of AI copilot features.

The experiment design is as follows: while deploying the AI copilot, the company randomly selected half (34) of the 68 business areas in this city as the control group and disabled the AI copilot on the app for all agents in the control group. Agents in the control group

saw a notification in the app interface indicating that the AI copilot feature was under maintenance and temporarily unavailable. This small-scale RCT experiment lasted until the end of 2019 (approximately 11 months). Although this RCT experiment provided cleaner estimation results, it is not suitable as our primary identification strategy for three reasons: First, the data firm only provided us with the transaction dataset for the city and did not provide the supply-side, demand-side, and feedback datasets. Second, the sample size of the RCT experiment was relatively small, with around 4,000 transaction records. Third, we were unable to isolate the effects of AI copilot on the supply-side and demand-side functions from this RCT experiment. Therefore, we only consider this RCT experiment as a supplementary part of our identification strategy.

Table A10 shows the estimation results. We can see that relative to the control group, the deployment of the AI copilot significantly decreases the time on market for both sellers and buyers in the treatment group, while housing transaction prices increase significantly. In terms of magnitude, time on market for sellers decreased by 9.8% $\left(\frac{0.37}{3.773}\right)$ relative to its pre-treatment mean of 3.773, time on market for buyers decreased by 19.3% $\left(\frac{0.45}{2.331}\right)$ relative to its pre-treatment mean of 2.331, and housing transaction prices increased by 0.81% $\left(\frac{0.08}{9.843}\right)$ relative to its pre-treatment mean of 9.843.

To further verify whether the firm's RCT experiment adhered to randomization, we conduct randomization checks by testing whether the main variables have significant differences during the pre-treatment period. The randomization check results are reported in Appendix Table A11, showing that there were no significant differences in the characteristics of the main variables between the treatment and control groups before the experiment. This confirms that the selection of the treatment and control groups in the RCT experiment was random. Hence, the supplementary RCT analysis results are qualitatively similar to the overall impact results, further supporting the robustness of our main findings and confirming our identification strategy.

5 Mechanisms

In this section, we conduct a series of analyses to further explore the mechanisms driving the overall impact, focusing on the specific functions of the AI copilot in supporting agents on both the demand-side (buyers) and the supply-side (sellers).

5.1 Demand-Side: Optimal Recommendation

First, one key function of AI copilot for supporting agents on the demand-side (buyers) is providing optimal housing recommendations. [11] The logic behind the optimal housing recommendations mechanism is that when AI copilot assists agents in recommending housing options more aligned with buyers' preferences, buyers will be more satisfied with the options. This satisfaction will reduce buyers' subsequent search efforts and time spent, thereby decreasing time on the market for both buyers and sellers. Regarding housing transaction prices, on the one hand, more satisfactory housing options will reduce buyers' search efforts, resulting in a smaller consideration set and making it harder for them to find a house at a lower price, all else being equal. On the other hand, satisfied buyers will also reduce their on-site bargaining efforts, leading to lower on-site discounts. Both of the two channels are likely to increase housing transaction prices.

To test this mechanism, we first examine whether AI copilot decreases the number of on-site housing viewings per week, which reflects buyers' search efforts. [12]. We replace the dependent variable with $Viewing$ and re-estimate Eq (1).[13] The estimation results reported in Column (1) of Table 5 show that the deployment of AI copilot indeed decrease on-site viewings. Further, the estimation results in Column (2) show that the negative effect of AI copilot on on-site viewings is driven by the demand-side function. In terms of magnitudes, average access to the demand-side AI copilot reduces on-site housing viewings by 0.148 (-

[11] This function's app interface is displayed in Part (a) of Figure 1.

[12] On-site viewing is a crucial step in buyers' housing search process.

[13] $Viewing$ is the number of times a property is viewed on-site by buyers per week in the demand-side dataset.

0.3814×0.388), representing a 9.25% decrease from the pre-treatment mean of 1.6. The event studies displayed in (a) and (b) of Figure A2 also support the parallel trends assumption. We also examine the effect of AI copilot on transaction volume by replacing the dependent variable with Log_volume, which represents the weekly transaction volume at the business area level, and re-estimating Eq (1). The results shown in (c) and (d) of Figure A3 and Table A13 indicate that AI copilot does not have a significant impact on transaction volume. This provides further evidence that the negative effects of AI copilot on on-site viewings indeed stem from reduced search efforts from buyers, supporting our prediction.

We then replace the dependent variable with Log_listed_price to examine whether the reduction in buyers' search efforts leads to higher last listed prices for the houses they ultimately transact. The estimation results reported in Columns (3) and (4) of Table 5 show that the deployment of AI copilot has a positive and statistically significant effect on the last listed prices of transacted houses. The magnitude in Column (3) indicates that average access to AI copilot increases Log_listed_price by 0.148 (0.1089×0.446), a 1.4% increase from the pre-treatment mean of 10.57. The event studies are displayed in (c) and (d) of Figure A2.

Next, we replace the dependent variable with Discount, which represents the discount buyers receive during on-site bargaining. If the housing recommendations from AI copilot better meet buyers' needs, buyers will exert less effort during on-site bargaining, thereby leading to a smaller discount (which also explains the positive impact of AI copilot on transaction prices). The estimation results reported in Table A14 show that AI copilot significantly reduces on-site discounts. The magnitude in Column (1) indicates that AI copilot reduces the on-site discount by 0.004 (0.01×0.446), up a 11% increase from the pre-treatment mean of 0.035. The event studies are displayed in (e) and (f) of Figure A3.

To provide more direct evidence that AI copilot assists agents in providing more optimal housing recommendations for buyers, we examine whether buyers' feedback on housing recommendations becomes more positive following the deployment of AI copilot. Thus, we replace the dependent variable with Recomm_optimal, which takes the value of 1 if buy-

ers select "high-quality recommendation" in the feedback system, and 0 otherwise. The estimation results presented in Column (1) of Table 6 show that the deployment of AI copilot significantly increases the likelihood that buyers select "high-quality recommendation" label. In terms of magnitudes, average access to the demand-side AI copilot improves Recomm_optimal by 0.158 (0.3540×0.446), a 38% increase from the pre-treatment mean of 0.412. Column (1) of Table A15 shows that the demand-side function of AI has a positive and statistically significant impact on Recomm_optimal. The event studies are displayed in Figure A4. Therefore, buyers' feedback provides more direct evidence supporting our optimal housing recommendation mechanism.

Finally, we are also interested in how the housing recommendation function of AI copilot affects the distribution of buyers' search attention. We predict that the personalized housing recommendations provided by AI copilot can lead to a more diversified search attention from buyers, reducing search congestion caused by agents' own recommendation biases (inertia). To test this, we replace the dependent variable with Sd(viewing), which measures the standard deviation of on-site viewing counts for listed houses at the community level each week, and re-estimate Eq (1). The estimation results presented in Appendix Table A12 show that although the coefficient on Post×Ratio_tran is negative and statistically insignificant (see Column (1)), the coefficient on Post×Ratio_buyer is negative and statistically insignificant (see Column (2)). The event studies are displayed in (a) and (b) of Figure A3. Hence, the demand-side function of the AI copilot does indeed make buyers' search efforts more diversified, further supporting the prediction that the AI copilot facilitates more personalized recommendations.

5.2 Demand-Side: Improved Communication Quality

In this section, we examine another function of the AI copilot in supporting agents on the demand side (buyers), which is to improve the communication quality by providing agents

with optimal answer scripts.[14] If the AI copilot helps agents respond better to buyers' questions and provides better communication quality, this can lead to quicker conversion of potential buyers into actual buyers by effectively guiding them through the purchase process. This can also enhance buyers' trust in the agents. However, measuring whether an agent's answer script is optimal is challenging. Fortunately, the structured data from buyers' feedback labels and textual review data provide a feasible approach to quantify whether the answer scripts are optimal from the buyers' perspective.

First, one of the labels that buyers can select in the feedback system to evaluate agents is "communication inefficiency". If the AI copilot assists agents in providing an optimal answer script, the likelihood of buyers selecting the "communication inefficiency" label should decrease. We replace the dependent variable with Talk_Inefficiency, which takes the value of 1 if buyers select the "communication inefficiency" label in the feedback system, and 0 otherwise. The estimation results presented in Column (1) of Table 6 show that the deployment of the AI copilot significantly reduces the likelihood of buyers selecting the "communication inefficiency" label. Column (1) of Table A15 shows that the demand-side function of AI also has a negative and statistically significant impact on Talk_Inefficiency. The event study is displayed in (c) of Figure A4.

Next, we directly quantify whether buyers' textual reviews include positive evaluations of agents' communication skills. Specifically, we use the ChatGPT API to identify whether each review contains a positive evaluation of the agent's communication skills. [15] Then, we create a new variable, Talk_Comfort, which takes the value of 1 if the review contains a positive evaluation of the agent's communication skills, and 0 otherwise. We replace the dependent variable with Talk_Comfort and re-estimate Eq 1. The estimation results presented in Column (4) of Table 6 show that the deployment of the AI copilot significantly increases the likelihood that buyers positively evaluate the agent's communication skills in

[14]This function's app interface is displayed in Part (b) of Figure 1.

[15]We also used the BERT model to quantify this topic and filter for positive reviews, yielding very similar results.

their review. Column (4) of Table A15 shows that the demand-side function of AI also has a positive and statistically significant impact on Talk_Comfort. The event study is displayed in (d) of Figure A4.

Furthermore, we investigate whether the AI copilot's demand-side function positively affects buyers' trust in agents, thereby providing indirect evidence for the optimal answer script channel. We include a new variable, Trust, which takes the value of 1 if buyers select the "trustworthy" label in the feedback system, and 0 otherwise, and replace it as the dependent variable. The estimation results reported in Column (5) of Table 6 show that the estimated coefficient is positive and statistically significant, supporting our prediction. Similarly, the estimation results reported in Column (5) of Table A15 show that this effect is indeed realized through the demand-side function of the AI copilot. The event study is displayed in (e) of Figure A4.

One potential concern is that the agents' on-site communication and house presentation skills might confound the above two measures. However, the AI copilot's functionality does not help agents improve their on-site communication and house presentation skills. Therefore, the impact of AI copilot on buyers' feedback regarding agents' on-site communication and house presentation skills can serve as a placebo test. We replace the dependent variable with Intro_Well, which takes the value of 1 if buyers select the "clear and effective on-site house presentation" label in the feedback system, and 0 otherwise. The estimation results presented in Column (2) of Table 6 show that the deployment of the AI copilot has no significant effect on the likelihood that buyers select this label. Column (2) of Table A15 also shows that the impact of the demand-side function of AI on Intro_Well is insignificant, supporting this placebo test.

We also conduct four additional placebo tests. First, we include a new variable, Appearance, which takes the value of 1 if buyers select the "good appearance and temperament" label in the feedback system, and 0 otherwise, and replace it as the dependent variable. The estimation results reported in Column (6) of Table 6 show that the estimated coefficient

is insignificant, supporting our prediction. Next, since the optimal answer script function does not apply to sellers (supply side), we conduct the placebo test of the AI copilot on sellers' evaluations of Talk_Inefficiency, Talk_Comfort, and Trust. The estimation results reported in columns (3)-(5) of Table 8 show that the estimated coefficients are all insignificant, confirming that the placebo test passes.

5.3 Supply-Side: Strategic Pricing Adjustments

On the supply side, one of the functions of the AI copilot supporting agents is to recommend strategic price adjustments. [16] Specifically, the AI copilot makes suggestions to increase or decrease the listing price based on market trends, as well as past viewing and transaction data for the property and surrounding neighborhood. The logic behind this mechanism is that a more reasonable pricing strategy, aligned well with market conditions, will better attract buyers and reduce the time spent on searching and negotiating processes, thereby lowering the time on market for both buyers and sellers.

To test this mechanism, we first look at the total frequency and magnitude of price adjustments. Therefore, we introduce a new variable, Total_adjust_times, which represents the number of price adjustments made to the property each week. The estimation results reported in Columns (1) and (2) of Table 7 show that the estimated coefficient on Post×Ratio is positive and statistically significant. In terms of magnitude, for example, in Column (1), the average access to the AI copilot's supply-side function increases Total_adjust_times by 0.13 (0.0789×0.388), a 19% increase from its pre-treatment mean of 0.16. We then introduce Total_adjust_mag, which represents the magnitude of price adjustments. The estimation results reported in Columns (3) and (4) of Table 7 show that the AI copilot significantly reduces the magnitude of price adjustments. Average access to the AI copilot's supply-side function reduces Total_adjust_mag by 0.13 (-0.7386×0.388), a 6.8% reduction from its pre-treatment mean of 4.24. Taken together, the results provide evidence that the deployment of

[16] This function's app interface is displayed in (c) of Figure 1.

the AI copilot makes price adjustments more frequent and with smaller magnitudes, which may better align with optimal pricing.

Next, we further examine the frequency of upward and downward price adjustments and their respective magnitudes to understand how the price adjustment strategy works. We introduce four variables: Down_adjust_times, Down_adjust_mag, Up_adjust_times, and Up_adjust_mag, which represent 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. We replace these as dependent variables and re-estimate Eq (1). The estimation results reported in Columns (1) and (3) of Table A16 show that the positive effect of AI copilot on price adjustment frequency is driven by downward price adjustments. The estimation results reported in Columns (2) and (4) of Table A16 show that the negative effect of AI copilot on price adjustment magnitude is also driven by downward price adjustments.

Table A17 shows the effects of the AI copilot's supply-side and demand-side functions on the four price adjustment variables. The estimation results in Table A17 are qualitatively similar to those in Table A16 and driven by the supply-side function of the AI copilot, as shown by the coefficient on Post×Ratio_seller. In Column (1) of Table A17, the magnitude shows that average access to the AI copilot's supply-side function increases Down_adjust_times by 0.13 (0.0896×0.388), a 27% increase from its pre-treatment mean of 0.128. The magnitude in Column (4) of Table A17 shows that average access to the AI copilot's supply-side function reduces Up_adjust_mag by 8.4% (1.01×0.388), a 27% reduction from its pre-treatment mean of 4.64. The event studies are displayed in Figure A5. In sum, the AI copilot's price adjustment recommendations lead to price adjustments more frequent and relatively conservative, which helps to avoid the problem of excessively long transaction periods caused by unreasonable pricing.

To provide more direct evidence that the AI copilot leads agents to provide better price adjustment recommendations for sellers, we measure this from the perspective of sellers' eval-

uations. Fortunately, one of the labels in the sellers' feedback system is "reasonable price adjustment recommendations." Then, we include a new variable, Pricing_optimal, which takes the value of 1 if sellers select the "reasonable price adjustment recommendations" label in the feedback system, and 0 otherwise, and replace it as the dependent variable. The estimation results reported in Column (1) of Table 8 show that the estimated coefficient on Post×Ratio_tran is positive and statistically significant. In terms of magnitude, average access to the AI copilot increases the likelihood of sellers selecting the Pricing_optimal label by 0.094 (0.2111 × 0.446), a 31% increase from its pre-treatment mean of 0.3. The estimation results reported in Column (1) of Table A19 further show that the AI copilot's supply-side function significantly increases the likelihood that sellers select the "reasonable price adjustment recommendations" label, supporting our prediction. The event studies are displayed in (b) of Figure A6.

A potential concern is that changes in housing stock composition may partially drive our main supply-side results. To eliminate 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 the price adjustment dataset to see whether the deployment of the AI copilot significantly affects these main property characteristics. The estimation results presented in Table A18 show that all estimated coefficients on Post×Ratio_tran are insignificant, indicating that the housing stock composition has not been affected by the AI copilot, thus addressing this concern.

5.4 Supply-Side: Accurate Identification of Property Selling Points

On the supply side, the second functions of the AI copilot supporting agents is to recommend optimal property descriptions (listing titles) for sellers. The logic is that if the AI copilot can recommend an optimal property description, highlighting the property's attractive features, thus increasing its appeal to buyers. This can lead buyers to be more satisfied with the recommended properties, reducing the time on market for both buyers and sellers, and

increasing their willingness to pay.

To examine whether AI copilot results in more optimal property descriptions, we measure this from the perspective of sellers' evaluations of the property descriptions. Fortunately, one of the labels buyers can select in the feedback system is "accurately capturing the property's key selling points." Thus, we include a new variable, Sellpoint_Accuracy, which takes the value of 1 if buyers select the "accurately capturing the property's key selling points" label in the feedback system, and 0 otherwise, and replace it as the dependent variable. The estimation results reported in Column (2) of Table 8 show that the estimated coefficient on Post×Ratio_tran is positive and statistically significant. In terms of magnitude, average access to the AI copilot increases the likelihood of sellers selecting the Sellpoint_Accuracy label by 0.13 (0.2973×0.446), a 52% increase from its pre-treatment mean of 0.25. The estimation results in Column (2) of Table A19 further show that the supply-side function of the AI copilot significantly increases the likelihood that sellers select the "accurately capturing the property's key selling points" label. The event study is displayed in (b) of Figure A6.

If the optimal property description is a potential mechanism that highlights the property's key selling points and increases its appeal to buyers, then buyers' evaluations of the property recommendations should also become more positive. That is, the supply-side function of the AI copilot—recommending optimal property descriptions—should further positively affect buyers' evaluations of the property recommendations. To test this, we turn to Column (1) of Table A15, where we find that the estimated coefficient on Post×Ratio_buyer is indeed positive and statistically significant, supporting our conjecture.

Additionally, we conduct several placebo tests, including examining the impact of the AI copilot on sellers' evaluations of Talk_Inefficiency, Talk_Comfort, Trust, and Appearance, because the AI copilot does not provide an answer script recommendation function on the supply side. The estimation results reported in Columns (3)-(6) of Table 8 show that all estimated coefficients on Post×Ratio_tran are insignificant, supporting the validity of the

placebo tests.

6 Effects on Matching Quality

In this section, we investigate how the AI copilot support agents affect matching quality, in addition to matching efficiency. Matching quality can be reflected in the overall satisfaction ratings from buyers and sellers after a transaction is completed. Although the transaction is finished, matching quality remains important for the real estate agency's future revenue, as the overall satisfaction of both buyers and sellers directly impacts the company's word-of-mouth. While matching quality in housing transactions is difficult to measure directly, the company's feedback system includes ratings from buyers and sellers on their overall satisfaction with the corresponding transaction. The ratings can serve as an indirect measure of matching quality from both the demand and supply sides.

Therefore, we introduce the variables Rating (buyer) and Rating (seller), which represent the overall satisfaction ratings of buyers and sellers, respectively, and use them as dependent variables.[17] The estimation results are presented in Table A20. In Column (1), we see that the estimated coefficient on Post×Ratio_tran is positive and statistically significant, indicating that the deployment of the AI copilot significantly improves the overall ratings from buyers. In terms of magnitude, average access to the AI copilot increases ratings from buyers by 0.094 (0.1906×0.446), a 1.8% increase from its pre-treatment mean of 4.85. Column (2) shows that both the demand-side and supply-side functions of the AI copilot significantly improve ratings from buyers. This is because the AI copilot's supply-side functions, such as providing optimal price adjustment recommendations and listing descriptions, indirectly enhance the satisfaction of buyers with the recommended properties and overall service.

Column (3) shows that the deployment of the AI copilot significantly increases the overall ratings from sellers. In terms of magnitude, average access to the AI copilot increases ratings

[17] Ratings range from integers 1 to 5.

from sellers by 0.094 (0.3232 $\times$ 0.446), a 3% increase from its pre-treatment mean of 4.69. The estimated coefficients in Column (4) show that both the demand-side and supply-side functions of the AI copilot significantly improve ratings from sellers. This may be because the AI copilot's demand-side function helps buyers reduce their search and bargaining efforts, which in turn indirectly improves sellers' overall satisfaction with the transaction. The event studies displayed in Figure A7 show that pre-treatment trends remain parallel. Taken together, the deployment of the AI copilot improves matching quality in the housing transaction process from both the demand-side and supply-side functions.

7 Conclusion

In this paper, we provide novel empirical evidence on the effect of AI in a major two-sided market by studying the introduction of an AI copilot for real estate agents on China's largest real estate platform. Leveraging a difference-in-differences approach, complemented by a field experiment, we demonstrate that AI significantly increases market efficiency by reducing search times for buyers and listing durations for sellers, particularly benefiting less experienced agents. Although transaction prices increase, buyers do not seem worse off, as evidenced by improved satisfaction ratings and their market behavior, while sellers benefit from improved pricing strategies and improved listing description quality. Our findings underscore AI's potential to effectively reduce information and communication frictions, improving outcomes in two-sided marketplace settings.

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Figures

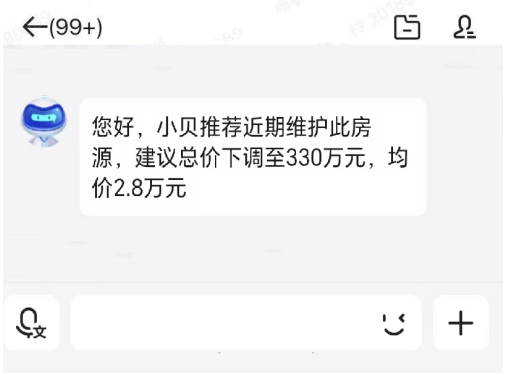
Figure 1: Sample AI Output: The App Interface for Agents



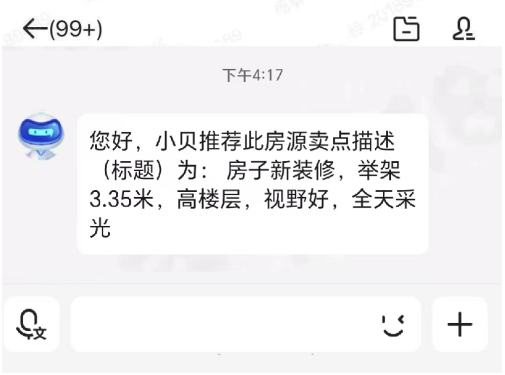
(a) AI-recommended Listings (Functioning for buyers)



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



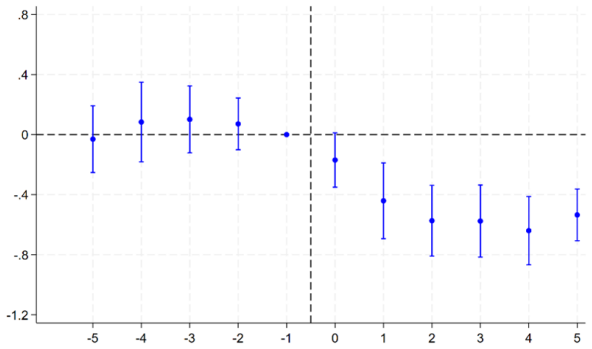
(c) AI-recommended Price adjustments (Functioning for Sellers)



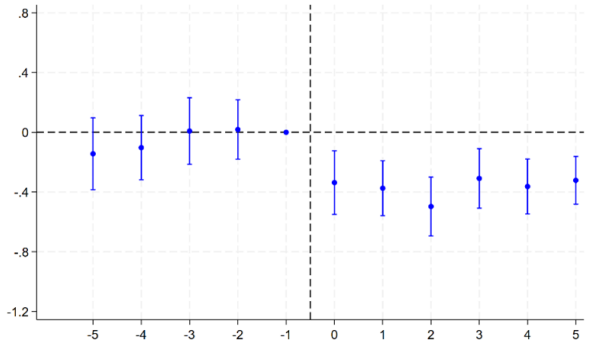
(d) AI-recommended Selling-point Descriptions (Functioning for Sellers)

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

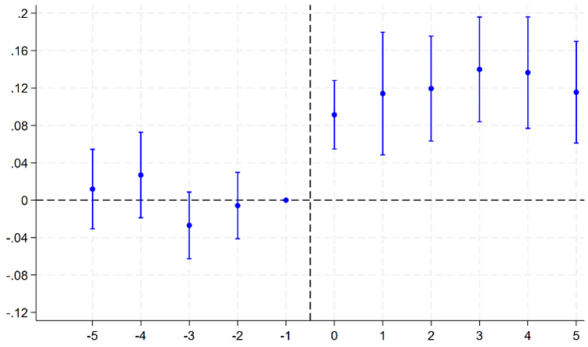
Figure 2: Event Studies for Main Outcomes: Total Effects of AI Adoption



(a) Log_days_seller (using Ratio_tran)



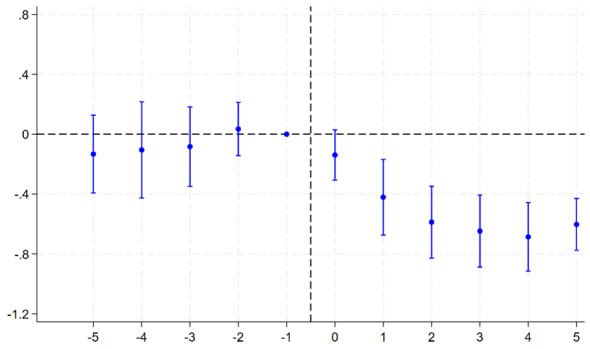
(b) Log_days_buyer (using Ratio_tran)



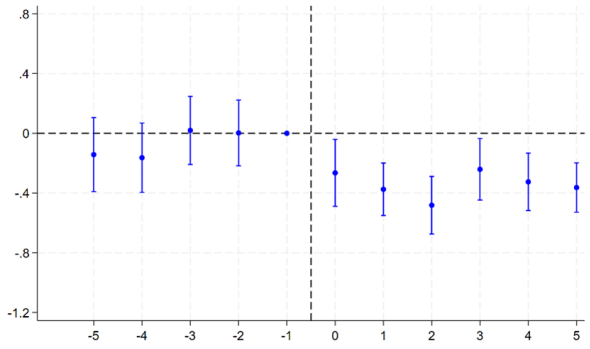
(c) Log_price (using Ratio_tran)

Notes. This figure plots the coefficients and 95% confidence intervals from event study regressions of adoption of AI on three main business outcomes: 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.

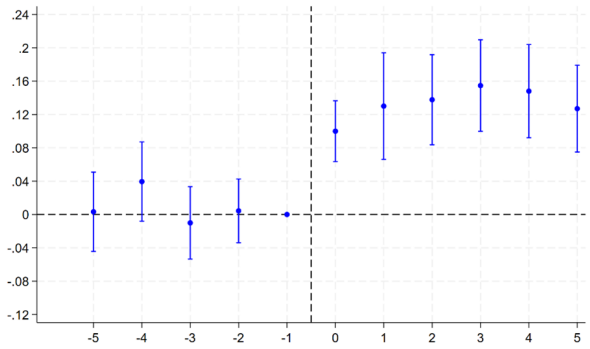
Figure 3: Event Studies for Main Outcomes: Demand-siede and Supply-side Effects of AI Adoption



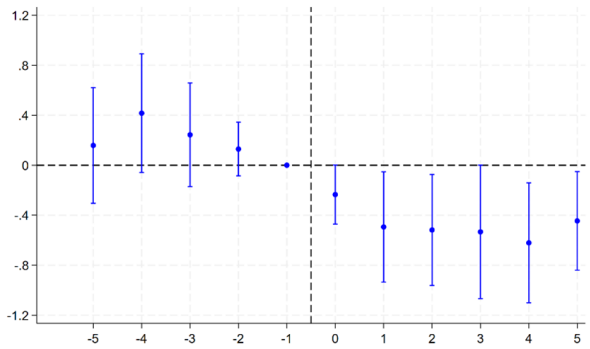
(a) Log_days_seller (using Ratio_buyer)



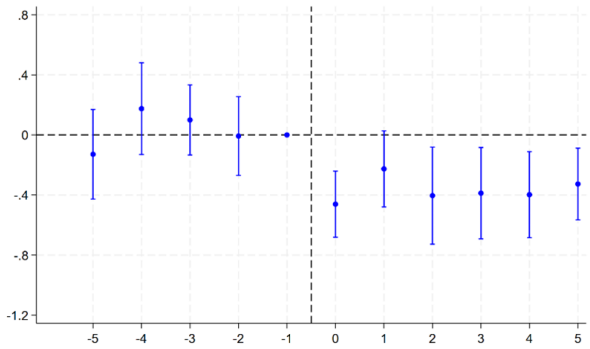
(b) Log_days_buyer (using Ratio_buyer)



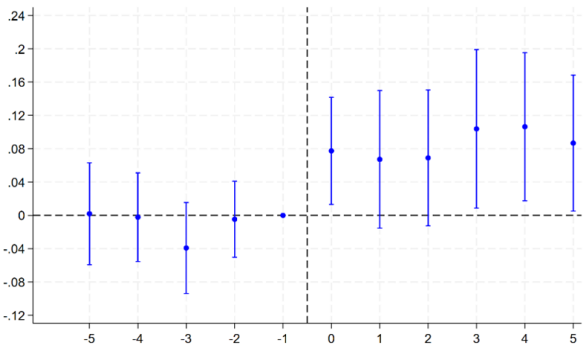
(c) Log_price (using Ratio_buyer)



(d) Log_days_seller (using Ratio_seller)



(e) Log_days_buyer (using Ratio_seller)



(f) Log_price (using 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: 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
Log_days_seller	3.986	1.261	2.197	4.111	5.541
Log_days_buyer	2.664	1.656	0	2.639	4.905
Log_price	10.274	0.763	9.326	10.267	11.275
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	0.091	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.

Table 2: Main Effects

VARIABLES	(1) Log_days_seller	(2) Log_days_buyer	(3) Log_price	(4) Log_days_seller	(5) Log_days_buyer	(6) Log_price
Post	1.3379***	0.3324	−0.0917*	1.3867***	0.3647*	−0.0963*
	(0.264)	(0.223)	(0.053)	(0.266)	(0.218)	(0.054)
Raito_tran	0.1819	0.3983***	−0.0858			
	(0.151)	(0.114)	(0.089)			
Post×Raito_tran	−0.5569***	−0.3073***	0.1201***			
	(0.131)	(0.060)	(0.023)			
Ratio_buyer				0.0867	0.3310**	−0.0300
				(0.141)	(0.129)	(0.066)
Post×Ratio_buyer				−0.2815***	−0.1679***	0.1261***
				(0.088)	(0.061)	(0.024)
Ratio_seller				0.3085	−0.0078	−0.1488
				(0.258)	(0.214)	(0.109)
Post×Ratio_seller				−0.5101**	−0.2757***	0.0104
				(0.201)	(0.086)	(0.028)
Observations	231,680	231,680	231,680	231,680	231,680	231,680
Adjusted R^2	0.083	0.128	0.948	0.083	0.128	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 the results of diff-in-diff regressions estimating the impact of AI adoption on the measures of 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, along with their interactions with variable *Post*. The definitions of variables are provided in Table 1 and Table A1. Standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Heterogeneity in the Effect of AI Adoption by Agents' Performance

VARIABLES	(1) Log_days_seller	(2) Log_days_buyer	(3) Log_price	(4) Log_days_seller	(5) Log_days_buyer	(6) Log_price
Post×Ratio_tran×Performance	0.1115***	0.0764***	-0.0017			
	(0.024)	(0.026)	(0.002)			
Post×Ratio_buyer×Performance				0.0976***	0.0609**	-0.0009
				(0.030)	(0.029)	(0.003)
Post×Ratio_seller×Performance				0.0750**	0.0466	-0.0018
				(0.031)	(0.030)	(0.004)
Observations	231,680	231,680	231,680	231,680	231,680	231,680
Adjusted R^2	0.084	0.129	0.948	0.084	0.129	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 estimation results relating main outcomes to the adoption of AI, examining heterogeneity by pre-treatment agents' performance. For brevity, we only report the triple interaction terms of interest. Performance is a variable that represents the performance score of agents in the company system during the pre-treatment period. 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 interactions with variable *Post*. The definitions of variables are provided in Table 1 and Table A1. Standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Heterogeneity in the Effect of AI Adoption by Agents' Tenure

VARIABLES	**(1)** Log_days_seller	**(2)** Log_days_buyer	**(3)** Log_price	**(4)** Log_days_seller	**(5)** Log_days_buyer	**(6)** Log_price
Post×Ratio_tran×Tenure	0.0229**	0.0245***	-0.0002			
	(0.009)	(0.007)	(0.001)			
Post×Ratio_buyer×Tenure				0.0239**	0.0151	-0.0004
				(0.010)	(0.010)	(0.001)
Post×Ratio_seller×Tenure				0.0053	0.0251**	0.0014
				(0.010)	(0.013)	(0.002)
Observations	231,680	231,680	231,680	231,680	231,680	231,680
Adjusted R^2	0.083	0.128	0.948	0.083	0.128	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 estimation results relating main outcomes to the adoption of AI, examining heterogeneity by pre-treatment agents' tenure. For brevity, we only report the triple interaction terms of interest. Tenure is a variable that represents the length of time agents have been employed at the company at the time of treatment. 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 interactions with variable *Post*. The definitions of variables are provided in Table 1 and Table A1. Standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Effects from Demand-side: on-site Viewing and Last Listed Prices

VARIABLES	(1) Viewing	(2) Viewing	(3) Log_listed_price	(4) Log_listed_price
Post	-1.3997***	-1.3498***	-0.0699	-0.0757
	(0.314)	(0.303)	(0.052)	(0.053)
Ratio_tran	0.0357		-0.0932	
	(0.222)		(0.091)	
Post×Ratio_tran	-0.2685*		0.1089***	
	(0.143)		(0.023)	
Ratio_buyer		0.2763		-0.0293
		(0.215)		(0.067)
Post×Ratio_buyer		-0.3814***		0.1109***
		(0.145)		(0.025)
Ratio_seller		-0.5567		-0.1590
		(0.360)		(0.113)
Post×Ratio_seller		0.0798		0.0174
		(0.172)		(0.028)
Observations	13,514,707	13,514,707	231,680	231,680
Adjusted R^2	0.092	0.092	0.950	0.950
Controls	Yes	Yes	Yes	Yes
City×Month FE	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes

Notes. This table presents the results of diff-in-diff regressions estimating the impact of AI adoption on demand-side measures, including the weekly on-site Viewing frequency of apartments and the last listed prices of sold properties. 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 interactions with variable *Post*. The definitions of variables are provided in Table 1 and Table A1. Standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Effects from Demand-side: Buyers' Feedback

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Recomm_optimal	Intro_well	Talk_inefficiency	Talk_comfort	Trust	Appearance
Post	-0.1269	-0.2923*	0.0705	-0.0505	-0.0394	-0.0646
	(0.246)	(0.166)	(0.043)	(0.036)	(0.042)	(0.200)
Ratio_tran	-0.1424	-0.0355	0.0153	-0.0051	-0.0339	0.0576
	(0.123)	(0.066)	(0.010)	(0.012)	(0.025)	(0.125)
Post×Ratio_tran	0.3540***	0.1060	-0.0465**	0.0734***	0.0652***	0.0022
	(0.100)	(0.067)	(0.018)	(0.028)	(0.023)	(0.087)
Observations	75,596	75,596	75,596	75,596	75,596	75,596
Adjusted R^2	0.203	0.182	0.039	0.048	0.044	0.216
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 on buyers' feedback. 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 interactions with variable *Post*. The definitions of variables are provided in Table 1 and Table A1. Standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Effects from Supply-side: Sellers' Price Adjustment Behaviors

VARIABLES	(1) Total_adjust_times	(2) Total_adjust_times	(3) Total_adjust_mag	(4) Total_adjust_mag
Post	-0.0450	-0.0513*	1.8442***	1.8048***
	(0.030)	(0.031)	(0.446)	(0.401)
Ratio_tran	-0.0288*		0.4764*	
	(0.015)		(0.261)	
Post×Ratio_tran	0.0549***		-0.2816*	
	(0.016)		(0.168)	
Ratio_buyer		-0.0107		-0.2263
		(0.019)		(0.266)
Post×Ratio_buyer		0.0149		0.3235
		(0.028)		(0.206)
Ratio_seller		-0.0411*		0.8837*
		(0.024)		(0.516)
Post×Ratio_seller		0.0789**		-0.7386***
		(0.031)		(0.245)
Observations	13,581,455	13,581,455	2,171,883	2,171,883
Adjusted R^2	0.027	0.027	0.055	0.055
Controls	Yes	Yes	Yes	Yes
City×Month FE	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes

Notes. This table presents the results of diff-in-diff regressions estimating the impact of AI adoption on sellers' price adjustment behaviors. The dependent variables, Total_adjust_times and Total_adjust_mag, represent the total weekly number of price adjustments and the magnitude of price adjustments for listed apartments, 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, along with their interactions with variable *Post*. The definitions of variables are provided in Table 1 and Table A1. Standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 8: Effects from Supply-side: Sellers' Feedback

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Pricing_optimal	Sellpoint_accur	Talk_inefficiency	Talk_comfort	Trust	Appearance
Post	-0.1574	-0.0080	0.0091	-0.0532	-0.0718	0.1242
	(0.321)	(0.325)	(0.024)	(0.039)	(0.101)	(0.221)
Ratio_tran	-0.0448	-0.0136	0.0534**	-0.0414***	0.0862***	-0.0703
	(0.083)	(0.085)	(0.026)	(0.015)	(0.024)	(0.086)
Post×Ratio_tran	0.2111***	0.2973***	-0.0149	0.0017	-0.0143	-0.0314
	(0.062)	(0.088)	(0.009)	(0.008)	(0.025)	(0.081)
Observations	20,336	20,336	20,336	20,336	20,336	20,336
Adjusted R^2	0.128	0.135	0.024	0.049	0.122	0.145
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 on sellers' feedback. 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 interactions with variable *Post*. The definitions of variables are provided in Table 1 and Table A1. Standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix A. Table and Figure

Figure A1: Flow chart

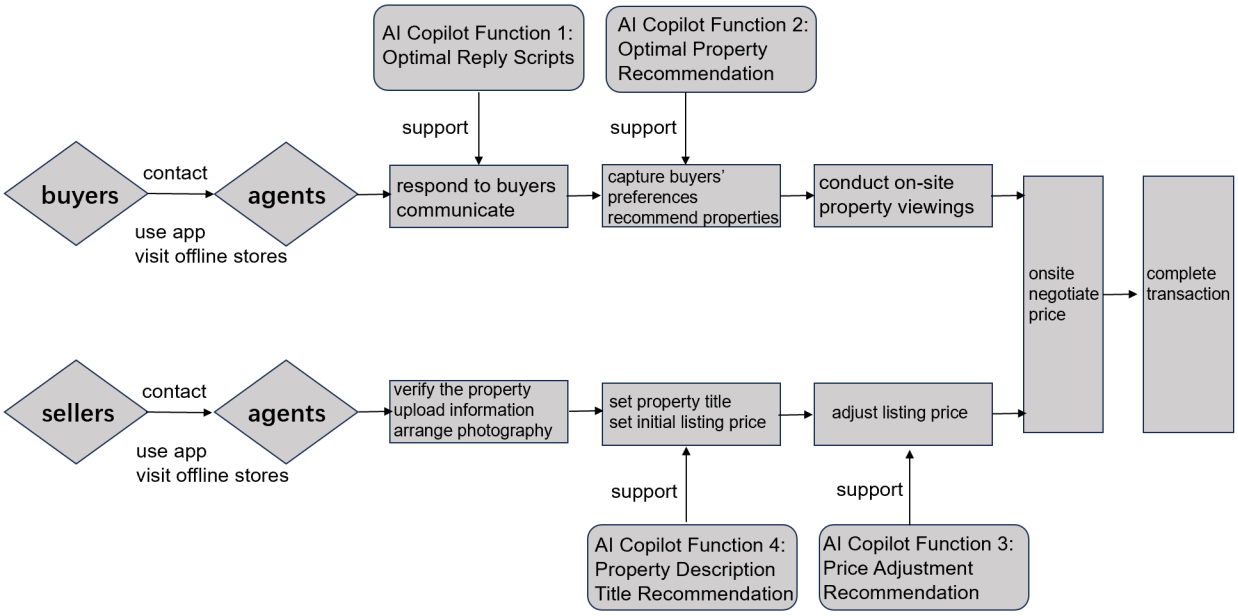


Table A1: Additional Summary statistics

	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	1.646	2.879	0	1	4
Sd(viewing)	1.507	1.675	0	1	3.502
Log_volume	1.365	0.63	0.693	1.099	2.303
Num_list	233.495	228.641	42	166	495
Textual feedback (buyer)					
Rating	4.884	0.392	5	5	5
recommend_optimal	0.368	0.482	0	0	1
Intro_well	0.093	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	0.426	0.494	0	0	1
Textual feedback (seller)					
Rating	4.693	0.632	4	5	5
Pricing_optimal	0.255	0.436	0	0	1
sellingpoint_accuracy	0.241	0.427	0	0	0
Talk_inefficiency	0.005	0.071	0	0	0
Talk_comfort	0.009	0.093	0	0	0
Trust	0.047	0.213	0	0	0
Appearance	0.249	0.432	0	0	1

Notes. This table presents summary statistics for the additional variables in the demand-side and supply-side datasets (which include 13,514,707 and 13,581,455 data points, respectively), as well as buyers' and sellers' evaluation data in the feedback system (which contain 75,596 and 20,336 data points, respectively).

Table A2: Main Effects: Full Table

VARIABLES	(1) Log_days_seller	(2) Log_days_buyer	(3) Log_price	(4) Log_days_seller	(5) Log_days_buyer	(6) Log_price
Post	1.3379***	0.3324	-0.0917*	1.3867***	0.3647*	-0.0963*
	(0.264)	(0.223)	(0.053)	(0.266)	(0.218)	(0.054)
Ratio_tran	0.1819	0.3983***	-0.0858			
	(0.151)	(0.114)	(0.089)			
Post×Ratio_tran	-0.5569***	-0.3073***	0.1201***			
	(0.131)	(0.060)	(0.023)			
Ratio_buyer				0.0867	0.3310**	-0.0300
				(0.141)	(0.129)	(0.066)
Post×Ratio_buyer				-0.2815***	-0.1679***	0.1261***
				(0.088)	(0.061)	(0.024)
Ratio_seller				0.3085	-0.0078	-0.1488
				(0.258)	(0.214)	(0.109)
Post×Ratio_seller				-0.5101**	-0.2757***	0.0104
				(0.201)	(0.086)	(0.028)
Population	0.0001	0.0003	0.0002	-0.0000	0.0003	0.0002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Post×Population	0.0003	0.0001	-0.0001**	0.0003	0.0001	-0.0001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment	-0.0220	0.0933	0.0059	-0.0006	0.1171	0.0073
	(0.087)	(0.081)	(0.042)	(0.086)	(0.083)	(0.042)
Post×Unemployment	-0.0429	0.0247	0.0016	-0.0648	0.0130	0.0040
	(0.062)	(0.047)	(0.013)	(0.055)	(0.045)	(0.013)
Gdp	0.0000	0.0121**	0.0135***	-0.0006	0.0109*	0.0130***

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VARIABLES	**(1)** Log_days_seller	**(2)** Log_days_buyer	**(3)** Log_price	**(4)** Log_days_seller	**(5)** Log_days_buyer	**(6)** Log_price
	(0.008)	(0.006)	(0.003)	(0.009)	(0.006)	(0.004)
Post×Gdp	0.0005	0.0025	0.0017**	0.0012	0.0028	0.0018**
	(0.005)	(0.003)	(0.001)	(0.005)	(0.003)	(0.001)
Income	0.0917	-0.0202	0.0547**	0.0928	-0.0187	0.0545**
	(0.065)	(0.035)	(0.025)	(0.066)	(0.034)	(0.025)
Post×Income	-0.1306***	-0.0346	0.0074	-0.1353***	-0.0374	0.0067
	(0.037)	(0.025)	(0.005)	(0.037)	(0.025)	(0.005)
Building size	0.0060***	0.0044***	-0.0009***	0.0060***	0.0044***	-0.0009***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Building age	0.0242***	-0.0414**	-0.0025	0.0242***	-0.0413**	-0.0025
	(0.008)	(0.019)	(0.002)	(0.008)	(0.019)	(0.002)
Floor	0.0271***	-0.0042	-0.0086***	0.0271***	-0.0042	-0.0086***
	(0.008)	(0.003)	(0.002)	(0.008)	(0.003)	(0.002)
Decoration	-0.1316***	-0.0059	0.0511***	-0.1316***	-0.0058	0.0511***
	(0.009)	(0.007)	(0.003)	(0.009)	(0.007)	(0.003)
Room	-0.0600***	0.0538***	0.0336***	-0.0602***	0.0539***	0.0337***
	(0.013)	(0.008)	(0.007)	(0.013)	(0.008)	(0.007)
School	-0.1638	0.1610	-0.1325**	-0.1266	0.1807	-0.1142*
	(0.186)	(0.150)	(0.065)	(0.187)	(0.153)	(0.069)
Subway	-0.0062	0.0097	0.0120**	-0.0065	0.0095	0.0120**
	(0.008)	(0.010)	(0.005)	(0.008)	(0.010)	(0.005)
Constant	3.1761***	1.5974***	9.7463***	3.0995***	1.5963***	9.7597***
	(0.417)	(0.277)	(0.160)	(0.430)	(0.276)	(0.153)

—*continued on next page*—

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VARIABLES	(1) Log_days_seller	(2) Log_days_buyer	(3) Log_price	(4) Log_days_seller	(5) Log_days_buyer	(6) Log_price
Observations	231,680	231,680	231,680	231,680	231,680	231,680
Adjusted R^2	0.083	0.128	0.948	0.083	0.128	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 the Full results of diff-in-diff regressions estimating the impact of AI adoption on the measures of 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, along with their interactions with variable *Post*. The definitions of variables are provided in Table 1 and Table A1. Standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Robustness to Alternative Clustering

VARIABLES	(1) Log_days_seller	(2) Log_days_buyer	(3) Log_price	(4) Log_days_seller	(5) Log_days_buyer	(6) Log_price
Post	1.3379***	0.3324	-0.0917*	1.3867***	0.3647	-0.0963*
	(0.268)	(0.227)	(0.053)	(0.271)	(0.223)	(0.054)
Ratio_tran	0.1819	0.3983***	-0.0858			
	(0.147)	(0.107)	(0.089)			
Post×Ratio_tran	-0.5569***	-0.3073***	0.1201***			
	(0.131)	(0.061)	(0.023)			
Ratio_buyer				0.0867	0.3310***	-0.0300
				(0.142)	(0.102)	(0.066)
Post×Ratio_buyer				-0.2815***	-0.1679***	0.1261***
				(0.089)	(0.062)	(0.024)
Ratio_seller				0.3085	-0.0078	-0.1488
				(0.251)	(0.211)	(0.108)
Post×Ratio_seller				-0.5101**	-0.2757***	0.0104
				(0.205)	(0.090)	(0.028)
Observations	231,680	231,680	231,680	231,680	231,680	231,680
Adjusted R^2	0.083	0.128	0.948	0.083	0.128	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 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, along with their interactions with variable *Post*. The definitions of variables are provided in Table 1 and 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: Using Binary Ratios

VARIABLES	(1) Log_days_seller	(2) Log_days_buyer	(3) Log_price	(4) Log_days_seller	(5) Log_days_buyer	(6) Log_price
Post×Ratio_tran_high	-0.1877**	-0.1129***	0.0686***			
	(0.093)	(0.039)	(0.017)			
Post×Ratio_tran_low	0.1787***	0.1118***	-0.0119			
	(0.053)	(0.041)	(0.013)			
Post×Ratio_buyer_high				-0.0319	-0.0220	0.0408**
				(0.081)	(0.059)	(0.017)
Post×Ratio_buyer_low				0.1496**	0.0727	-0.0286**
				(0.072)	(0.059)	(0.012)
Post×Ratio_seller_high				-0.1795*	-0.0781	0.0289
				(0.108)	(0.062)	(0.021)
Post×Ratio_seller_low				0.0104	0.0168	0.0069
				(0.061)	(0.047)	(0.007)
Observations	231,680	231,680	231,680	231,680	231,680	231,680
Adjusted R^2	0.082	0.128	0.949	0.082	0.128	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 the results of difference-in-differences regressions estimating the impact of AI adoption on the main outcomes, with binary ratios based on quintiles. 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 interactions with variable *Post*. The definitions of variables are provided in Table 1 and Table A1. Standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Heterogeneity in the Effect of AI Adoption by Agents' Performance: Binary Variable

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Log_days_seller	Log_days_buyer	Log_price	Log_days_seller	Log_days_buyer	Log_price
Post×Ratio_tran×Perf_dum	0.3641***	0.2660***	−0.0026			
	(0.072)	(0.078)	(0.007)			
Post×Ratio_buyer×Perf_dum				0.3177***	0.2060***	0.0031
				(0.086)	(0.070)	(0.009)
Post×Ratio_seller×Perf_dum				0.2714***	0.1314	−0.0158
				(0.088)	(0.082)	(0.012)
Observations	231,680	231,680	231,680	231,680	231,680	231,680
Adjusted R^2	0.084	0.129	0.948	0.084	0.129	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 the estimation results linking the main outcomes to AI adoption, examining heterogeneity by agents' performance during pre-treatment period. For brevity, only the triple interaction terms of interest are reported. $Perf_dum$ is a binary variable that takes a value of 1 if the agent's score regarding performance is above the median and 0 otherwise. 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 interactions with variable *Post*. The definitions of variables are provided in Table 1 and Table A1. Standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Heterogeneity in the Effect of AI Adoption by Agents' Tenure: Binary Variable

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Log_days_seller	Log_days_buyer	Log_price	Log_days_seller	Log_days_buyer	Log_price
Post×Ratio_tran×Tenure_dum	0.2424***	0.1896***	-0.0031			
	(0.049)	(0.070)	(0.008)			
Post×Ratio_buyer×Tenure_dum				0.1051*	-0.0864	0.0007
				(0.062)	(0.060)	(0.005)
Post×Ratio_seller×Tenure_dum				-0.0947	0.0375	0.0006
				(0.074)	(0.076)	(0.006)
Observations	231,680	231,680	231,680	231,680	231,680	231,680
Adjusted R^2	0.083	0.128	0.948	0.083	0.128	0.949
City×Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the estimation results linking the main outcomes to AI adoption, examining heterogeneity by agents' tenure. For brevity, only the triple interaction terms of interest are reported. *Tenure_dum* is a binary variable that takes a value of 1 if the agent's tenure is above the median and 0 otherwise. 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 interactions with variable *Post*. The definitions of variables are provided in Table 1 and Table A1. Standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A7: Heterogeneity in the Effect of AI Adoption by Agents' Gender

VARIABLES	**(1)** Log_days_seller	**(2)** Log_days_buyer	**(3)** Log_price	**(4)** Log_days_seller	**(5)** Log_days_buyer	**(6)** Log_price
Post×Ratio_tran×Gender	0.0523	-0.0266	-0.0115			
	(0.052)	(0.069)	(0.011)			
Post×Ratio_buyer×Gender				0.0586	-0.0166	-0.0116
				(0.072)	(0.082)	(0.017)
Post×Ratio_seller×Gender				0.0056	0.0165	-0.0098
				(0.151)	(0.094)	(0.033)
Observations	231,680	231,680	231,680	231,680	231,680	231,680
Adjusted R^2	0.083	0.128	0.948	0.083	0.128	0.949
City×Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the estimation results linking the main outcomes to AI adoption, examining heterogeneity by agents' gender. For brevity, only the triple interaction terms of interest are reported. *Gender* is a binary variable, taking a value of 1 if the agent is male and 0 otherwise. 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 interactions with variable *Post*. The definitions of variables are provided in Table 1 and Table A1. Standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A8: Heterogeneity in the Effect of AI Adoption by Agents' Education

VARIABLES	**(1)** Log_days_seller	**(2)** Log_days_buyer	**(3)** Log_price	**(4)** Log_days_seller	**(5)** Log_days_buyer	**(6)** Log_price
Post×Ratio_tran×Education	0.1600*	-0.1039	-0.0173			
	(0.089)	(0.097)	(0.015)			
Post×Ratio_buyer×Education				0.2323	-0.2403	0.0025
				(0.207)	(0.163)	(0.024)
Post×Ratio_seller×Education				-0.0273	0.1910	-0.0422
				(0.345)	(0.239)	(0.032)
Observations	231,680	231,680	231,680	231,680	231,680	231,680
Adjusted R^2	0.086	0.128	0.948	0.086	0.128	0.949
City×Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the estimation results linking the main outcomes to AI adoption, examining heterogeneity by agents' education during the pre-treatment period. For brevity, only the triple interaction terms of interest are reported. *Education* is a binary variable indicating the agent's educational background, taking a value of 1 if the agent graduated from a key university and 0 otherwise. 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 interactions with variable *Post*. The definitions of variables are provided in Table 1 and 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 Market Thickness from Supply Side

VARIABLES	(1) Log_days_seller	(2) Log_days_buyer	(3) Log_price	(4) Log_days_seller	(5) Log_days_buyer	(6) Log_price
Post×Ratio_tran×Num_list	0.0006**	0.0002	-0.0001*			
	(0.000)	(0.000)	(0.000)			
Post×Ratio_buyer×Num_list				0.0003	-0.0000	-0.0001
				(0.000)	(0.000)	(0.000)
Post×Ratio_seller×Num_list				0.0007	0.0004	-0.0000
				(0.001)	(0.000)	(0.000)
Observations	231,680	231,680	231,680	231,680	231,680	231,680
Adjusted R^2	0.084	0.128	0.949	0.084	0.128	0.949
City×Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the estimation results linking the main outcomes to AI adoption, examining heterogeneity by the number of listed properties in the business area during the pre-treatment period. For brevity, only the triple interaction terms of interest are reported. Num_list is a variable representing the number of listed properties with the same number of rooms as the sold property in the business area during the pre-treatment period.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 interactions with variable *Post*. The definitions of variables are provided in Table 1 and Table A1. Standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A10: RCT Analysis

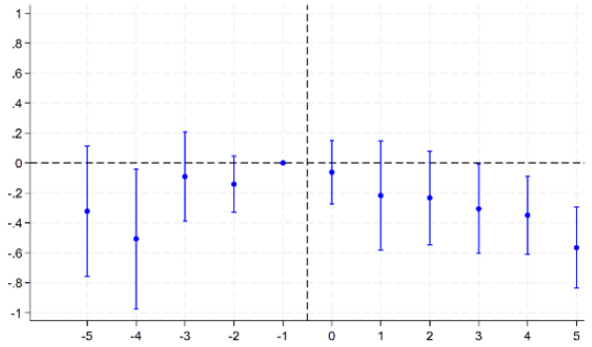
VARIABLES	(1) Log_days_seller	(2) Log_days_buyer	(3) Log_price
Post	0.4739***	0.4712***	-0.1084***
	(0.064)	(0.090)	(0.015)
o.Treat	-	-	-
Post×Treat	-0.3704***	-0.4506***	0.0817***
	(0.096)	(0.121)	(0.017)
Building size	0.0074***	0.0074***	-0.0003
	(0.001)	(0.002)	(0.000)
Building age	-0.0152	0.0329	-0.0239***
	(0.018)	(0.023)	(0.007)
Floor	0.0838***	0.0049	-0.0245***
	(0.027)	(0.032)	(0.004)
Decoration	-0.1246***	0.0531	0.0369***
	(0.031)	(0.043)	(0.005)
Room	-0.0625	-0.0877*	0.0420***
	(0.050)	(0.050)	(0.014)
Constant	3.5247***	1.6621***	9.8326***
	(0.143)	(0.139)	(0.042)
Observations	4,031	4,031	4,031
Adjusted R^2	0.100	0.033	0.650
District×Month FE	Yes	Yes	Yes
Location FE	Yes	Yes	Yes

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

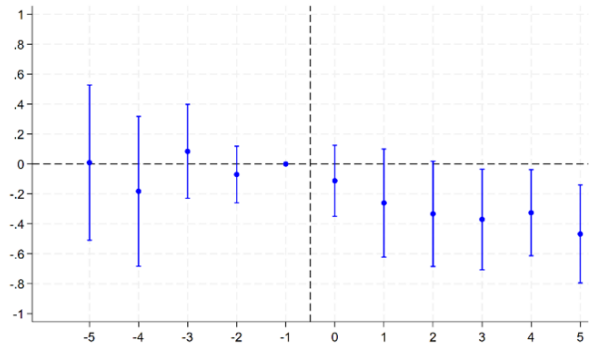
Table A11: Randomization Check

VARIABLE	Treatment Group	Control Group	p-Value of T-Test
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
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

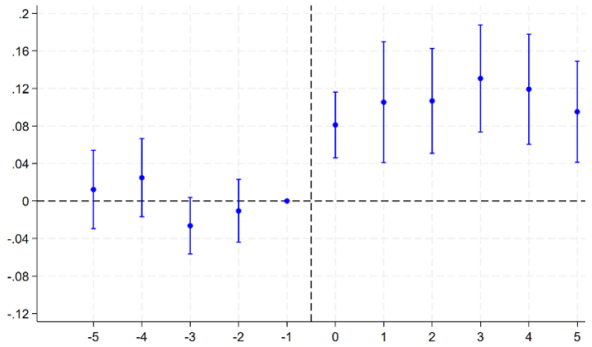
Figure A2: Event Studies for Effects from Demand-side: on-site Viewing and Last Listed Prices



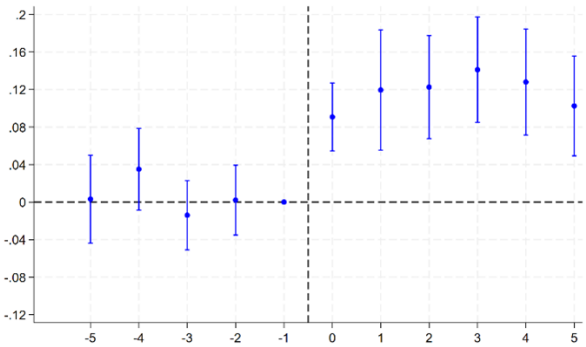
(a) Viewing (using Ratio_tran)



(b) Viewing (using Ratio_buyer)



(c) Log_listed_price (using Ratio_tran)



(d) Log_listed_price (using Ratio_buyer)

Notes. This figure plots the coefficients and 95% confidence intervals from event study regressions of adoption of AI on demand-side: including the weekly on-site viewing frequency of apartments and the last listed prices of sold properties. The specification follows Eq (1) and includes location and City×Month fixed effects. Robust standard errors are clustered at the district level.

Table A12: Effects from Demand-side: Standard Deviation of on-site Viewings

	(1)	(2)
VARIABLES	Sd(viewing)	Sd(viewing)
Post	-1.5049***	-1.4830***
	(0.352)	(0.335)
Ratio_tran	-0.0860	
	(0.249)	
Post×Ratio_tran	-0.1119	
	(0.124)	
Ratio_buyer		0.1791
		(0.220)
Post×Ratio_buyer		-0.2791**
		(0.117)
Ratio_seller		-0.2868
		(0.417)
Post×Ratio_seller		0.1986
		(0.159)
Observations	1,732,648	1,732,648
Adjusted R^2	0.203	0.204
Controls	Yes	Yes
City×Month FE	Yes	Yes
Location FE	Yes	Yes

Notes: This table presents the results of diff-in-diff regressions estimating the impact of AI adoption on standard deviation of buyers' on-site viewings at the business area level. The dependent variable, Sd(viewing), represent the standard deviation of buyers' on-site viewings at the business area level. 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 interactions with variable *Post*. The definitions of variables are provided in Table 1 and Table A1. Standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A13: Effects on Transaction Volumes

VARIABLES	**(1)** Log_volume	**(2)** Log_volume
Post	-0.0487	-0.0626
	(0.278)	(0.278)
Ratio_tran	0.1452	
	(0.109)	
Post×Ratio_tran	-0.0836	
	(0.126)	
Ratio_buyer		0.1469
		(0.109)
Post×Ratio_buyer		-0.1211
		(0.124)
Ratio_seller		0.1237
		(0.195)
Post×Ratio_seller		0.0632
		(0.180)
Observations	58,968	58,968
Adjusted R^2	0.620	0.620
Controls	Yes	Yes
City×Month FE	Yes	Yes
Location FE	Yes	Yes

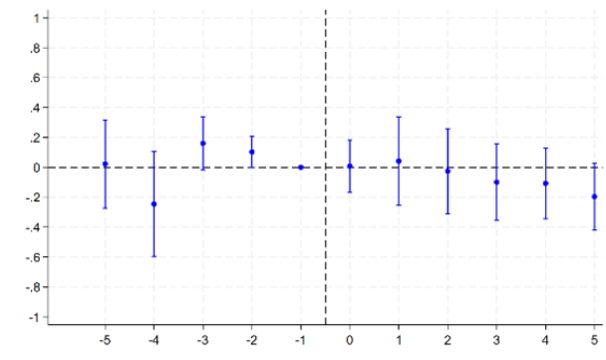
Notes: This table presents the results of diff-in-diff regressions estimating the impact of AI adoption on transaction volumes at the business area level. The dependent variable, Log_volume, represent weekly transaction volumes at the business area level. All columns include location and City×Month fixed 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 interactions with variable *Post*. The definitions of variables are provided in Table 1 and Table A1. Standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A14: Effects on on-site Discount

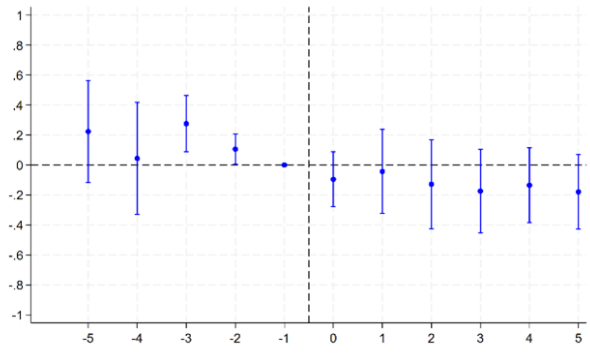
	(1)	(2)
VARIABLES	Discount	Discount
Post	0.0202***	0.0192***
	(0.005)	(0.005)
Ratio_tran	-0.0080	
	(0.006)	
Post×Ratio_tran	-0.0100***	
	(0.003)	
Ratio_buyer		-0.0007
		(0.005)
Post×Ratio_buyer		-0.0132***
		(0.004)
Ratio_seller		-0.0081
		(0.008)
Post×Ratio_seller		0.0055
		(0.004)
Observations	231,680	231,680
Adjusted R^2	0.090	0.090
Controls	Yes	Yes
City×Month FE	Yes	Yes
Location FE	Yes	Yes

Notes: This table presents the results of diff-in-diff regressions estimating the impact of AI adoption on on-site discounts. The dependent variable, Discount, represents the on-site discount of the transaction, calculated as the last listed price of the property minus the transaction price, divided by the last listed price. 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 interactions with variable *Post*. The definitions of variables are provided in Table 1 and Table A1. Standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

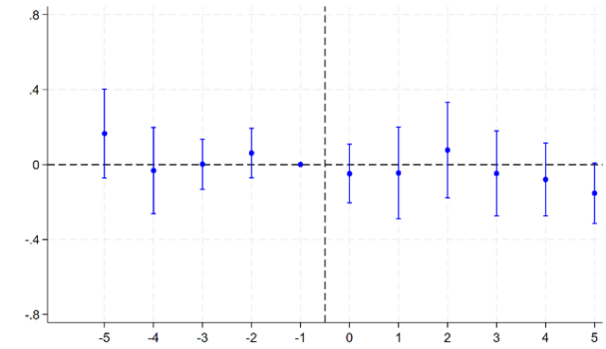
Figure A3: Effects for Demand-side: Sd(viewing), Transaction Volume, and Discount



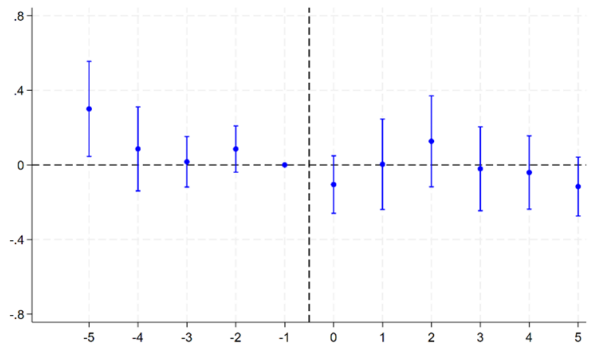
(a) Sd(viewing) (using Ratio_tran)



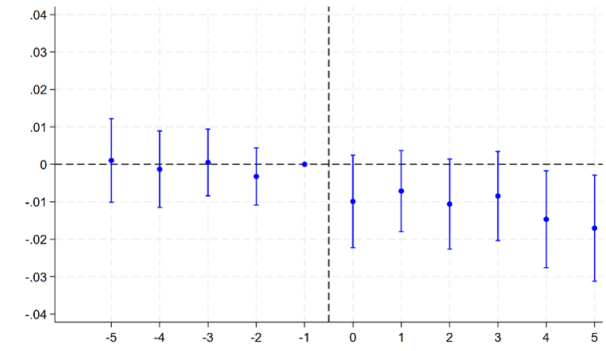
(b) Sd(viewing) (using Ratio_buyer)



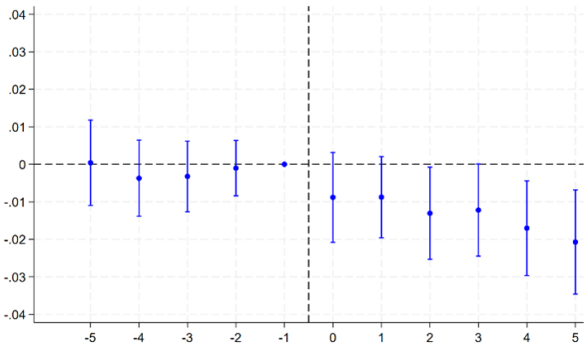
(c) Transaction Volume (using Ratio_tran)



(d) Transaction Volume (using Ratio_buyer)



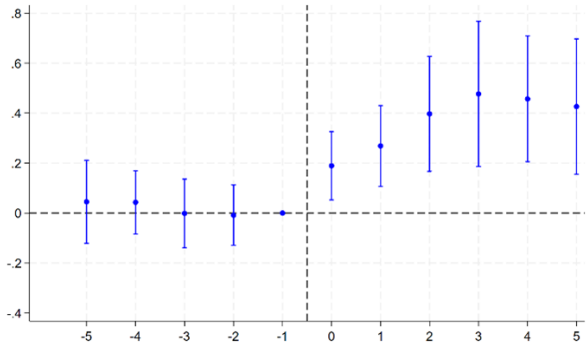
(e) Discount (using Ratio_tran)



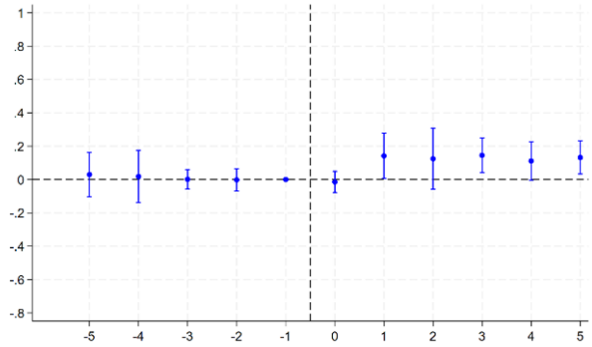
(f) Discount (using Ratio_buyer)

Notes. This figure plots the coefficients and 95% confidence intervals from event study regressions of adoption of AI on demand-side: Sd(viewing), volume, and discount from demand-side. The specification follows Eq (1) and includes location and City×Month fixed effects. Robust standard errors are clustered at the district level.

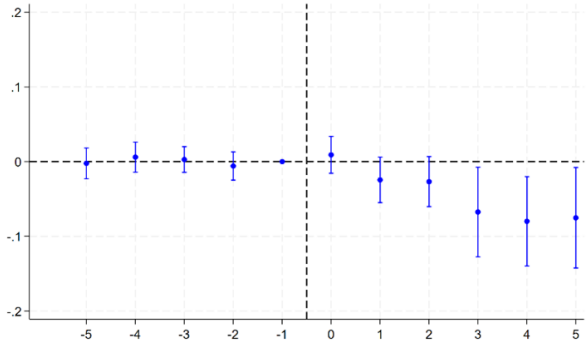
Figure A4: Event Studies for Effects on Buyers' Feedback



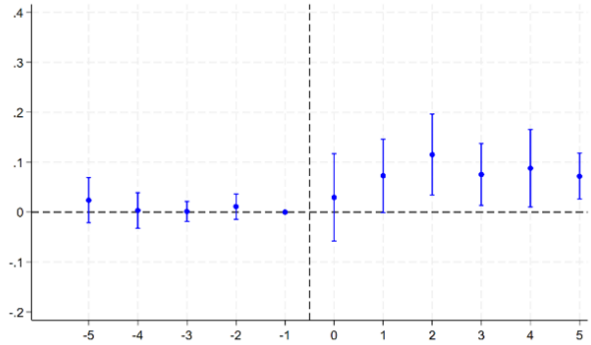
(a) recommend_optimal (using Ratio_tran)



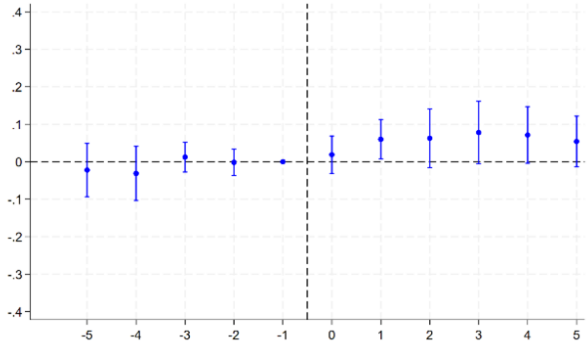
(b) Intro_well (using Ratio_tran)



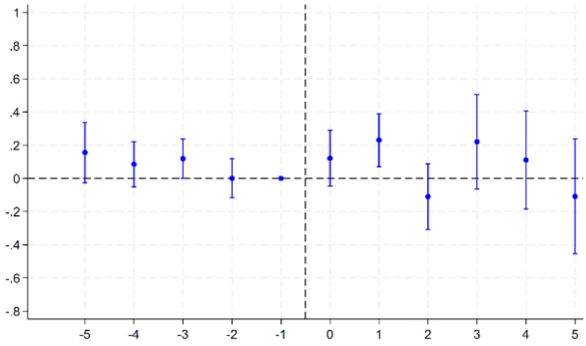
(c) Talk_inefficiency (using Ratio_tran)



(d) Talk_comfort (using Ratio_tran)



(e) Trust (using Ratio_tran)



(f) 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.

Table A15: Effects from Demand-side: Buyers' Feedback

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Recomm_optimal	Intro_well	Talk_inefficiency	Talk_comfort	Trust	Appearance
Post	-0.1203	-0.2983*	0.0460	-0.0001	-0.0085	-0.1454
	(0.214)	(0.165)	(0.040)	(0.031)	(0.043)	(0.206)
Ratio_buyer	-0.3233**	0.0938	0.0222**	-0.0066	0.0027	-0.1597
	(0.143)	(0.081)	(0.009)	(0.013)	(0.029)	(0.153)
Post×Ratio_buyer	0.2267**	0.0537	-0.0476***	0.0758***	0.0658***	-0.0175
	(0.107)	(0.071)	(0.013)	(0.026)	(0.024)	(0.070)
Ratio_seller	0.2211	-0.2015***	-0.0049	-0.0037	-0.0587**	0.3385**
	(0.148)	(0.065)	(0.011)	(0.012)	(0.027)	(0.148)
Post×Ratio_seller	0.2170**	0.0740	-0.0046	-0.0048	0.0102	0.0830
	(0.091)	(0.059)	(0.012)	(0.013)	(0.011)	(0.065)
Observations	75,596	75,596	75,596	75,596	75,596	75,596
Adjusted R^2	0.203	0.182	0.040	0.049	0.045	0.216
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City×Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes

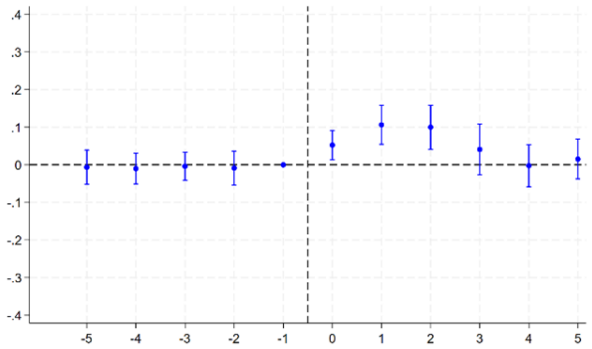
Notes: This table presents the results of diff-in-diff regressions estimating the impact of AI adoption on buyers' feedback. All columns include location and City×Month fixed effects. Controls include apartment characteristics (e.g., building age, number of rooms, etc.) as well as unemployment, population,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

Table A16: Effects from Supply-side: Sellers' Price Adjustment Behaviors: Split

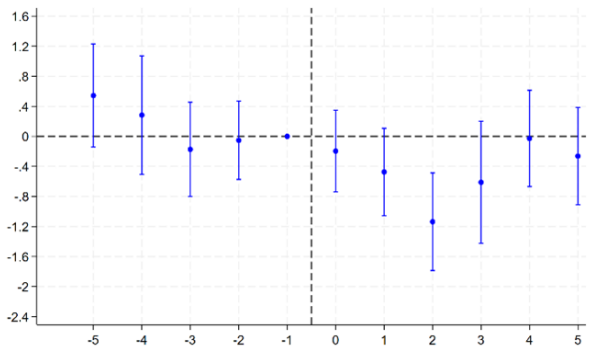
	(1)	(2)	(3)	(4)
VARIABLES	Down_adjust_times	Down_adjust_mag	Up_adjust_times	Up_adjust_mag
Post	-0.1466***	0.5430	0.1015***	2.7539***
	(0.039)	(0.411)	(0.020)	(0.675)
Ratio_tran	-0.0294**	0.3842	0.0006	0.6323
	(0.013)	(0.241)	(0.005)	(0.431)
Post×Ratio_tran	0.0520***	-0.1100	0.0029	-0.6687***
	(0.016)	(0.143)	(0.010)	(0.216)
Observations	13,581,455	1,807,297	13,581,455	491,030
Adjusted R^2	0.027	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 the results of diff-in-diff regressions estimating the impact of AI adoption on sellers' price adjustment behaviors. The dependent variables, Down_adjust_times and Down_adjust_mag, and Up_adjust_times and Up_adjust_mag, represent the weekly number of downward and upward price adjustments and the magnitude of those adjustments for listed apartments, 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, along with their interactions with variable *Post*. The definitions of variables are provided in Table 1 and Table A1. Standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

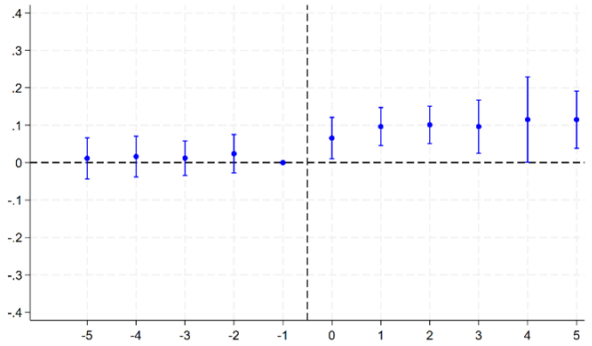
Figure A5: Event Studies for Sellers' Price Adjustment Behaviors



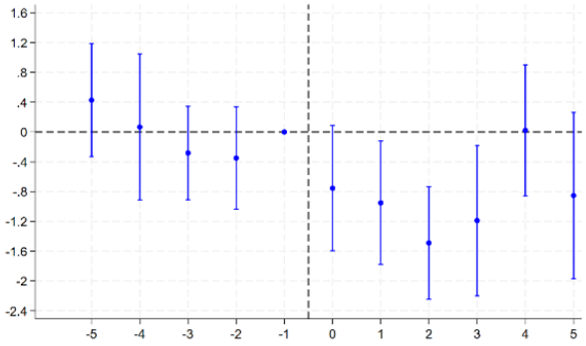
(a) Down_adjust_times (using Ratio_tran)



(b) Up_adjust_mag (using Ratio_tran)



(c) Down_adjust_times (using Ratio_seller)



(d) Up_adjust_mag (using Ratio_seller)

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

Table A17: Effects from Supply-side: Sellers' Price Adjustment Behaviors: Split

VARIABLES	(1) Down_adjust_times	(2) Down_adjust_mag	(3) Up_adjust_times	(4) Up_adjust_mag
Post	-0.1531***	0.4882	0.1019***	2.7178***
	(0.038)	(0.396)	(0.020)	(0.629)
Ratio_buyer	-0.0062	-0.1175	-0.0045	-0.5897*
	(0.017)	(0.273)	(0.006)	(0.323)
Post×Ratio_buyer	0.0059	0.3106	0.0090	0.1383
	(0.026)	(0.193)	(0.010)	(0.246)
Ratio_seller	-0.0529**	0.5934	0.0119*	1.6347*
	(0.023)	(0.488)	(0.007)	(0.849)
Post×Ratio_seller	0.0896***	-0.4360*	-0.0107	-1.0139***
	(0.031)	(0.245)	(0.010)	(0.259)
Observations	13,581,455	1,807,297	13,581,455	491,030
Adjusted R^2	0.027	0.060	0.015	0.047
Controls	Yes	Yes	Yes	Yes
City×Month FE	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes

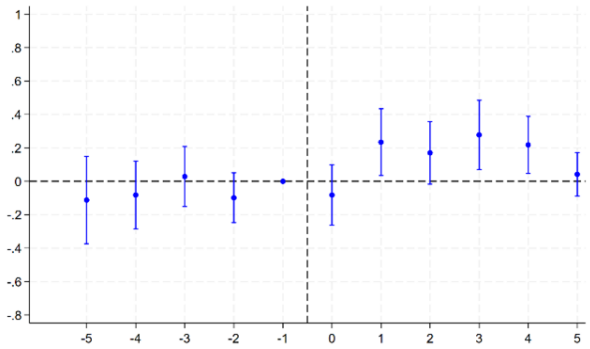
Notes: This table presents the results of diff-in-diff regressions estimating the impact of AI adoption on sellers' price adjustment behaviors. The dependent variables, Down_adjust_times and Down_adjust_mag, and Up_adjust_times and Up_adjust_mag, represent the weekly number of downward and upward price adjustments and the magnitude of those adjustments for listed apartments, 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, along with their interactions with variable *Post*. The definitions of variables are provided in Table 1 and Table A1. Standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A18: Effects on Composition of Listed Properties

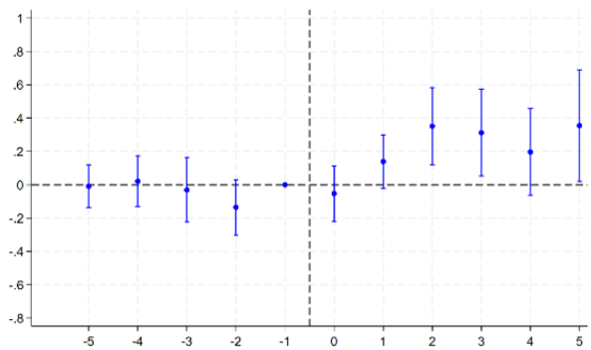
VARIABLES	(1) Building size	(2) Building age	(3) Floor	(4) Decoration	(5) Room
Post	0.0824***	0.1552***	-0.0351**	-0.0362**	-0.0033
	(0.031)	(0.034)	(0.017)	(0.014)	(0.010)
Ratio_tran	-0.1969	0.3051	-0.0774***	-0.0182	0.0716
	(0.183)	(0.310)	(0.028)	(0.087)	(0.111)
Post×Ratio_tran	-0.0104	-0.0007	0.0014	-0.0082	0.0007
	(0.009)	(0.015)	(0.006)	(0.005)	(0.004)
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, along with their interactions with variable *Post*. The definitions of variables are provided in Table 1 and Table A1. Standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

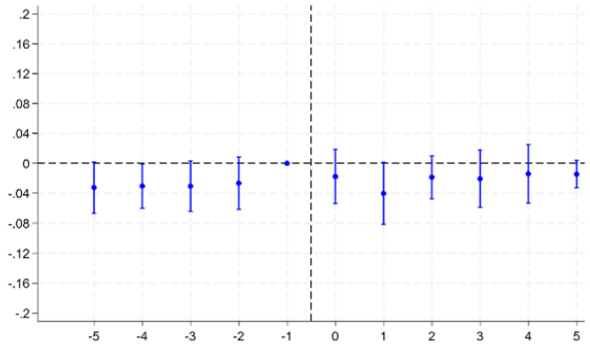
Figure A6: Event Studies for Effects on Sellers' Feedback



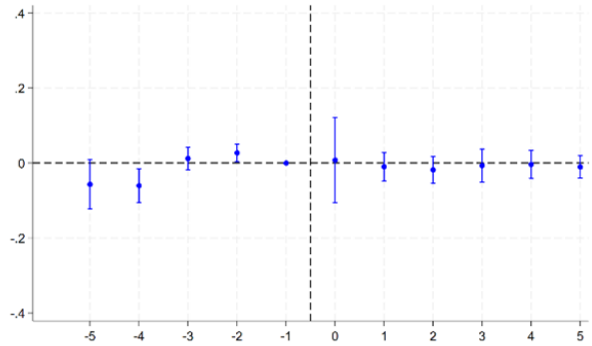
(a) Pricing_optimal (using Ratio_tran)



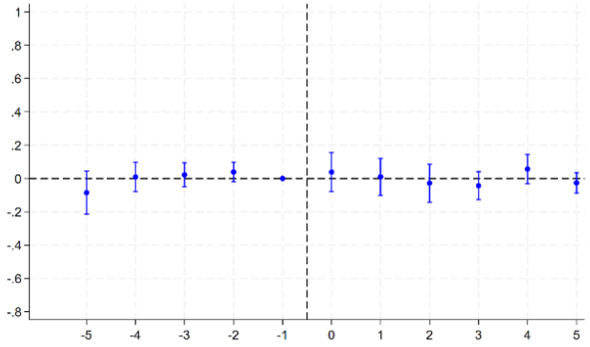
(b) sellingpoint_accuracy (using Ratio_tran)



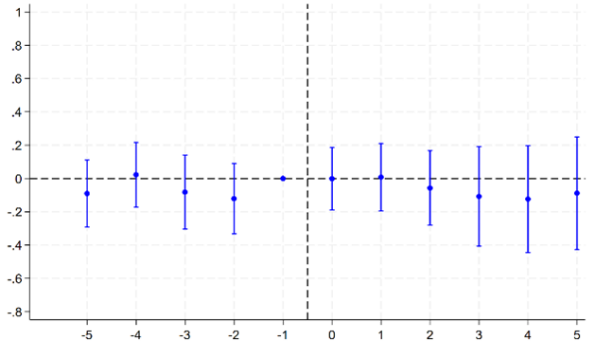
(c) Talk_inefficiency (using Ratio_tran)



(d) Talk_comfort (using Ratio_tran)



(e) Trust (using Ratio_tran)



(f) Appearance (using Ratio_tran)

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

Table A19: Effects from Supply-side: Sellers' Feedback

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Pricing_optimal	Sellpoint_accur	Talk_inefficiency	Talk_comfort	Trust	Appearance
Post	-0.2958	-0.1942	0.0027	-0.0527	-0.0647	0.1389
	(0.219)	(0.174)	(0.025)	(0.040)	(0.103)	(0.180)
Ratio_buyer	0.0680	0.0549	0.0512	-0.0556***	0.1080***	-0.1416
	(0.085)	(0.095)	(0.037)	(0.020)	(0.030)	(0.092)
Post×Ratio_buyer	0.0036	0.0948	-0.0115	0.0018	0.0034	0.0594
	(0.077)	(0.058)	(0.008)	(0.007)	(0.024)	(0.062)
Ratio_seller	-0.1833**	-0.1487	-0.0366	0.0229	-0.0430	0.2059
	(0.081)	(0.102)	(0.045)	(0.019)	(0.044)	(0.171)
Post×Ratio_seller	0.3343***	0.4328***	-0.0040	0.0004	-0.0213	-0.0653
	(0.067)	(0.061)	(0.008)	(0.007)	(0.023)	(0.073)
Observations	20,336	20,336	20,336	20,336	20,336	20,336
Adjusted R^2	0.131	0.141	0.023	0.049	0.122	0.145
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City×Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes

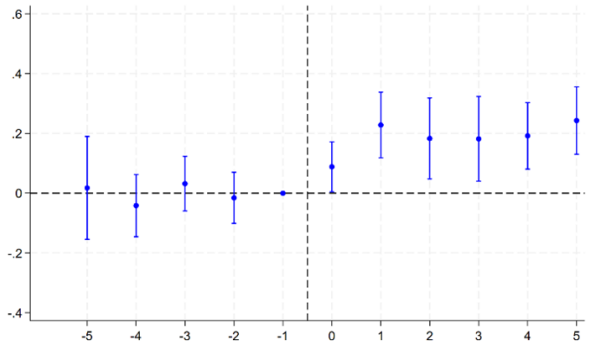
Notes: This table presents the results of diff-in-diff regressions estimating the impact of AI adoption on seller' feedback. All columns include location and City×Month fixed effects. Controls include apartment characteristics (e.g., building age, number of rooms, etc.) as well as unemployment, population,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

Table A20: Effects on Matching Quality: Rating from Buyers and Sellers

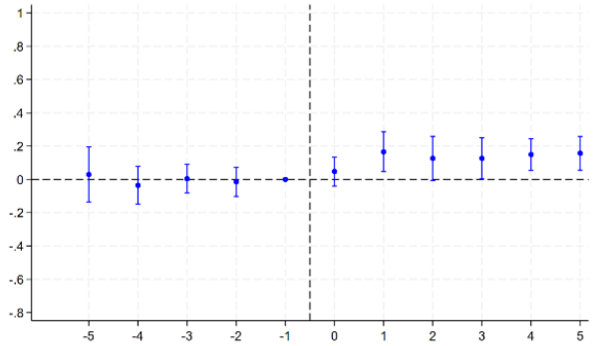
VARIABLES	(1) Rating(buyer)	(2) Rating(buyer)	(3) Rating(seller)	(4) Rating(seller)
Post	-0.0805	-0.0962	-0.3179	-0.2356
	(0.131)	(0.151)	(0.259)	(0.273)
Ratio_tran	-0.1012**		-0.2538	
	(0.048)		(0.189)	
Post×Ratio_tran	0.1906***		0.3232***	
	(0.048)		(0.064)	
Ratio_buyer		-0.0346		0.0518
		(0.056)		(0.255)
Post×Ratio_buyer		0.1213***		0.2927***
		(0.039)		(0.064)
Ratio_seller		-0.0458		-0.1843
		(0.051)		(0.273)
Post×Ratio_seller		0.1372***		0.1352**
		(0.049)		(0.060)
Observations	75,596	75,596	20,336	20,336
Adjusted R^2	0.049	0.049	0.080	0.081
Controls	Yes	Yes	Yes	Yes
City×Month FE	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes

Notes: This table presents the results of diff-in-diff regressions estimating the impact of AI adoption on ratings from buyers and sellers. 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 interactions with variable *Post*. The definitions of variables are provided in Table 1 and Table A1. Standard errors clustered at the district level are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

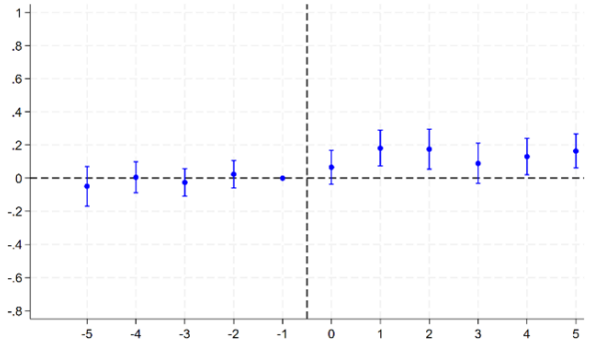
Figure A7: Event Studies for Buyers' and Sellers' Ratings



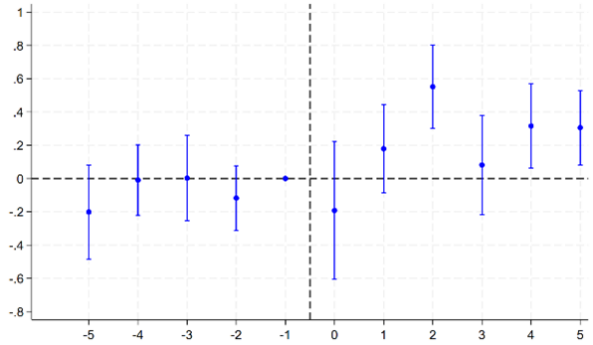
(a) Buyers' ratings (using Ratio_tran)



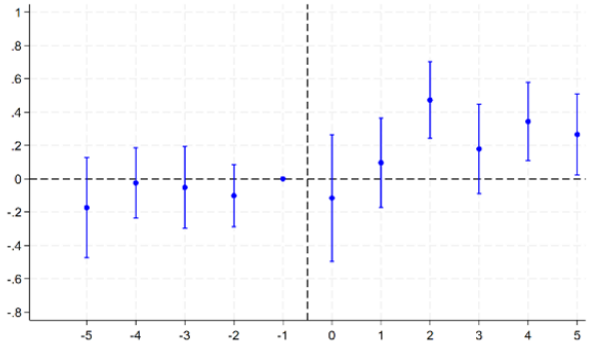
(b) Buyers' ratings (using Ratio_buyer)



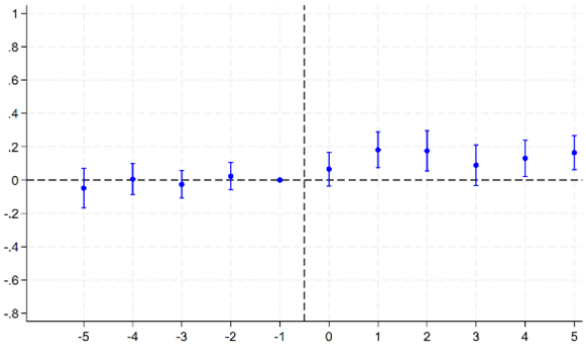
(c) Buyers' ratings (using Ratio_seller)



(d) Sellers' ratings (using Ratio_tran)



(e) Sellers' ratings (using Ratio_buyer)



(f) Sellers' ratings (using Ratio_seller)

Notes. This figure plots the coefficients and 95% confidence intervals from event study regressions of adoption of AI on 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.