AI Copilots in Real Estate: Evidence from China

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Motivation

➢ The advancement of AI technology has driven its rapid adoption across sectors (Maslej et al., 2025)

TURNING POINTS

A.I. Will Transform the Global Economy — if Humans Let It

We asked a group of business leaders to consider how businesses can benefit from artificial intelligence.

Generative AI at Work

By Erik Brynjolfsson, Danielle Li, Lindsey R. Raymond

November 2023| Working Paper No. 4141

Operations, Information & Technology

Motivation

- Why study AI Copilots in Two-Sided Markets?

  - Digital platforms increasingly adopt intermediaries-facing AI tools to assist real estate agents.
  - These AI copilots can influence matching, search frictions, and information asymmetry…

  - Yet the impact is theoretically ambiguous:
    - Potential efficiency gains (faster matches, better alignment of preferences).
    - Potential surplus redistribution (benefit for buyer or seller?).

- Understanding whether AI improves the market (or merely shifts surplus) is a first-order question.

- Real estate is a high-stakes, information-intensive market where these effects matter greatly.

Motivation

- Gaps in Existing Research

  - Existing studies mainly focus on buyer-facing/seller-facing algorithms (recommendation, pricing, ranking) (Raymond 2025, Allu et al., 2025, Zheng et al., 2025; Fong et al., 2025).

  - Literature on AI assistants primarily focuses call center, customer service, gig worker, general worker productivity, online shopping (Brynjolfsson et al., 2025; Zhang & Narayandas 2025; Sunet al., 2025; Hui et al., 2024)

  - Little is known about how intermediaries-facing AI copliot affects two-sided matching markets.

Motivation & Research Questions

- **Agent-facing AI** is rapidly being deployed to frontline decision-makers.
  - E.g., service reps, mortgage brokers, real estate agents.
- In **intermediated two-sided markets**, changing the intermediary's process can shift matching, speed, and prices jointly.
- Effects are ambiguous ex ante:
  - Frictions may fall $\rightarrow$ faster clearing, better decisions/experience.
  - But price and incidence are unclear $\rightarrow$ bargaining power and cross-side effects may change who captures value.
- This paper: an agent-facing copilot on a leading Chinese used-housing platform.
  - **Q1:** Effects on sale probability, time-on-market, prices, and experience?
  - **Q2:** Decompose into own-side vs cross-side effects (sheds light on value capture).

Institutional Setting – China's Resale Housing Market

- Data Infrastructure: Chinese brokerages typically own and guard their listing data.

- Governance Structure: Large firms in China directly employ agents (who earn salary plus commissions) and often intermediate both sides of a deal (dual agency)

- Platforms: Starting in the late 2010s, leading firms built integrated online–offline platforms/app.

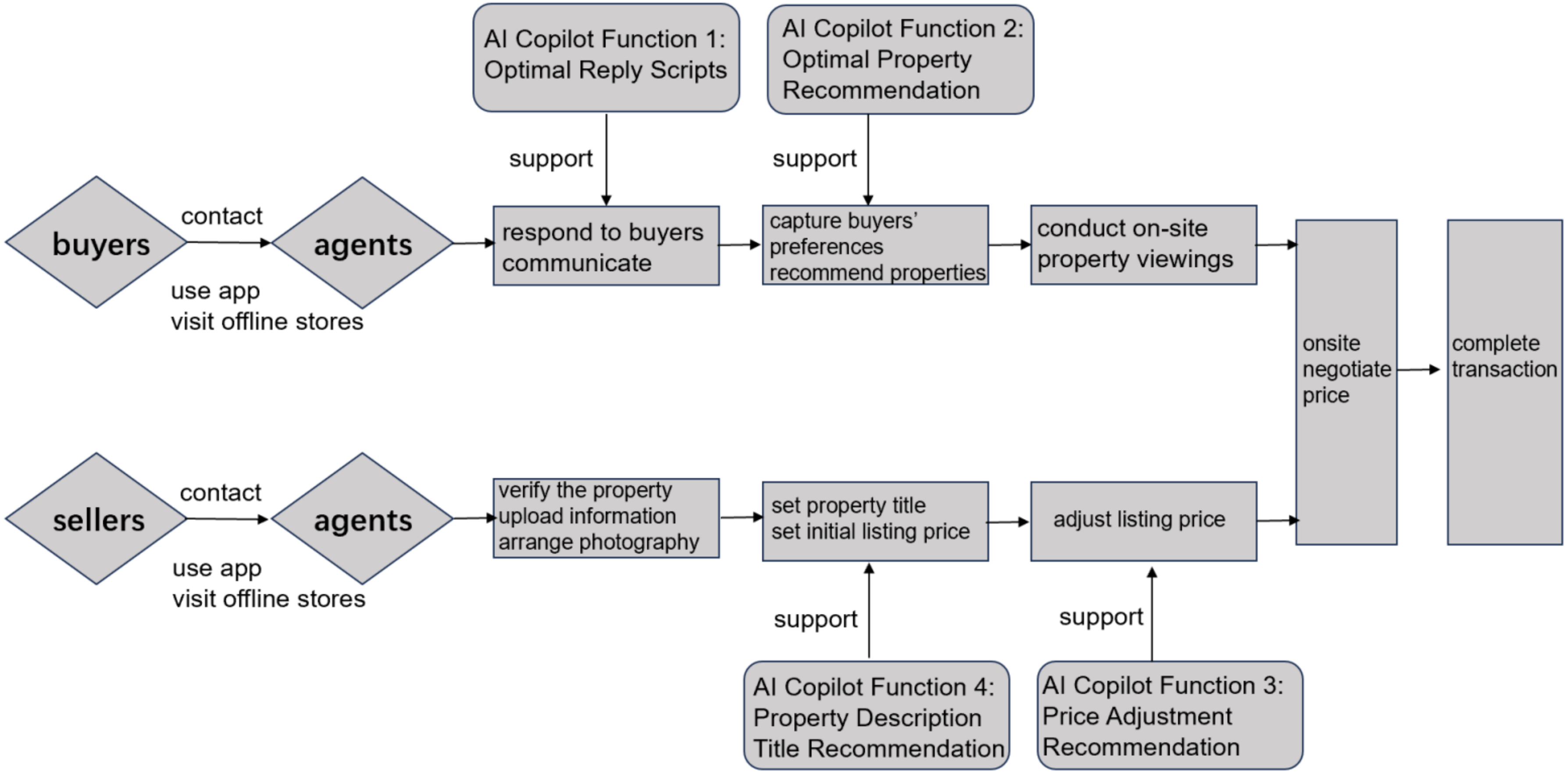
Institutional Setting

- We study one of the largest resale housing platforms.
  - Sellers list on this platform to access its verified, up-to-date inventory and buyer traffic.
  - Buyers use it for trusted, up-to-date listings and professional intermediation.
  - Transactions happen through both offline (walk-ins to a store, phone) and online (app/web) entry points.
  - The app is a central workflow when clients engage via the app, agents message, recommend homes, manage listings, and schedule viewings there.

- The AI copilot is designed to support agents' daily work and is available only within the app's agent–client chat interface.

The Typical Transaction Process on the Platform

Figure A1: Flow chart



Intervention: Agent-facing AI Copilot

- Platform-wide rollout on **Jan 16, 2019**.
- **Buyer workflow:** recommended listings + suggested reply scripts.
- **Seller workflow:** pricing guidance + suggested listing titles/descriptions.
- Tool is advisory and **visible only to agents**; clients affected through interactions.

Figure: Agent-buyer chat examples (recommended listings)

Preview of Results

Market Outcome

- **Market clears faster:** higher sell-within-3m; shorter seller time-on-market and buyer search duration (first contact on any listing $\rightarrow$ closing).
- **Two-sided effects:** Exposure on one side speeds outcomes on the other.
- **Prices rise and experience improves:** Price effects load mainly on **buyer-side** exposure; ratings improve.

Process Evidence

- **Buyer tools**: less viewings, recommendation/communication/trust labels improve.
- **Seller tools**: more frequent price adjustment with smaller magnitude, pricing/selling-point labels improve.

Taken together, the patterns are more consistent with reduced search/coordination frictions than with a purely redistributive shift in surplus.

Data & Outcomes

- Firm data (2018–2020): listings, transactions, ratings, weekly process variables.
- **Main outcomes:**
  - Sale within 3 months
  - Seller time-on-market; buyer search duration
  - Transaction price (log)
  - Buyer/seller ratings
- **Process proxies:**
  - On-site viewings
  - Price adjustment frequency and magnitude
  - Structured feedback labels (e.g., recommendations, communication, pricing advice)
- **Controls:**
  - Property characteristics: location, size, rooms, etc.
  - Local market conditions: unemployment, population, income, and GDP
- **Geography**: city$\rightarrow$district$\rightarrow$neighborhood (US analogue: state$\rightarrow$MSA$\rightarrow$county)

Research Design

- **Design 1 (RCT, Jinan):**
  Neighborhood-level random blocking of copilot access $\rightarrow$ causal effect of access.

- **Design 2 (18-city rollout):**
  Exposure DiD using pre-period app penetration $\rightarrow$ external validity $+$ side-specific decomposition.

RCT: Main Results

Main patterns: sale probability $\uparrow$, time-to-transaction $\downarrow$, prices $\uparrow$, ratings $\uparrow$ (in paper).

	Sold$<$ 3m	log Days (S)	log Days (B)	log Price
Post$\times$Treat	0.1106***	-0.3704***	-0.4506***	0.0476***
	(0.040)	(0.096)	(0.121)	(0.017)
Implied % change	–	-31%	-36%	4.8%
Control mean	0.5267	–	–	–
Observations	6,748	4,031	4,031	4,031
District$\times$Month FE	Yes	Yes	Yes	Yes
Neighborhood FE	Yes	Yes	Yes	Yes

Note: SE clustered at neighborhood level.

Exposure Measures (18-City Rollout Sample)

- Copilot is app-only $\rightarrow$ use pre-rollout app usage to proxy differential post-rollout reach.
- District-level predetermined exposure proxies:
  - `Ratio_tran`: pre-period share of transactions via app.
  - `Ratio_buyer`: pre-period share of buyers via app.
  - `Ratio_seller`: pre-period share of sellers via app.
- Interpretation: proxies for differential reach of buyer- vs seller-side workflows after rollout.

Rollout Exposure DiD

Overall effect:

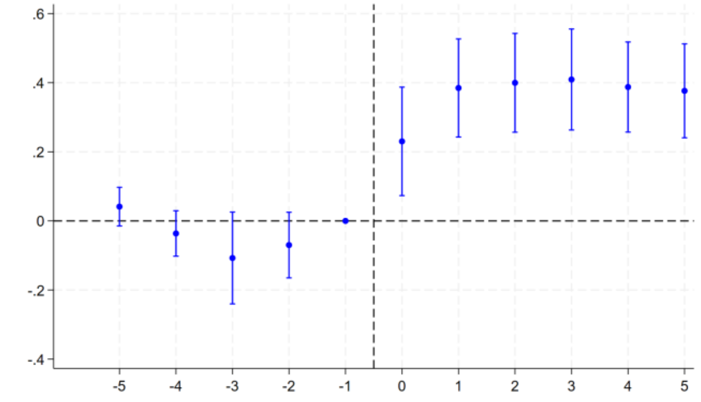
$$y_{indct} = \beta \, \text{Post}_t \times \text{Ratio\_tran}_d \; + \; X'_{idt}\delta \; + \; \xi_n \; + \; \tau_{ct} \; + \; \varepsilon_{indct}.$$

Side-specific decomposition:

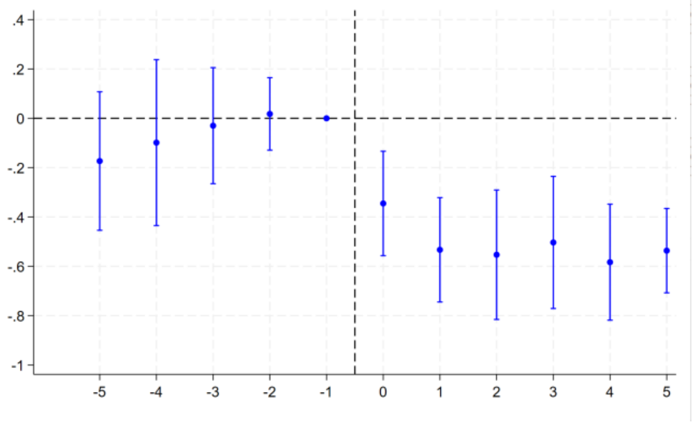
$$y_{indct} = \beta_B \, \text{Post}_t \times \text{Ratio\_buyer}_d + \beta_S \, \text{Post}_t \times \text{Ratio\_seller}_d + X'_{idt}\delta + \xi_n + \tau_{ct} + \varepsilon_{indct}.$$

- Controls + neighborhood FE (ξ_n) + city×month FE (τ_{ct}); cluster at district level.
- Key identifying assumption: exposure-weighted parallel trends.
- First stage: copilot usage increases strongly with baseline app penetration.

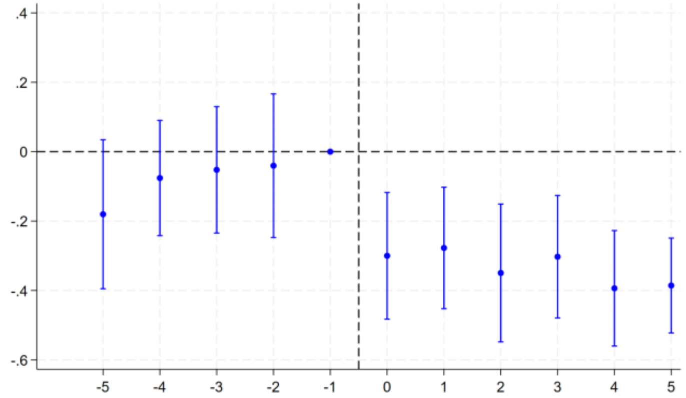
Event Study (Overall Exposure)



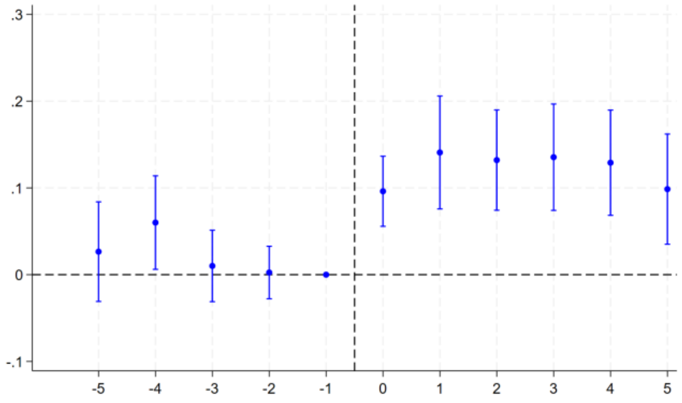
(a) Sold< 3m



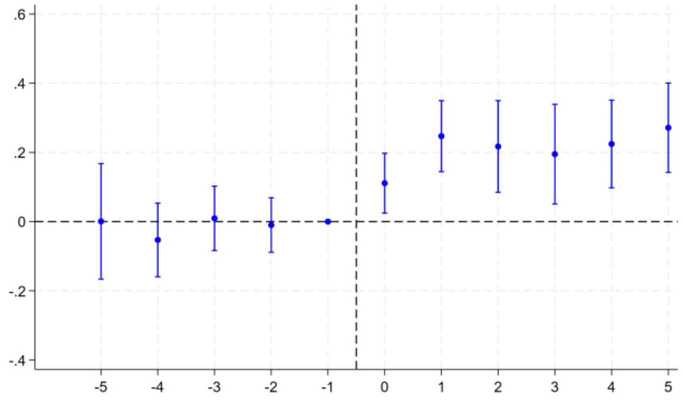
(b) log Days (Seller)



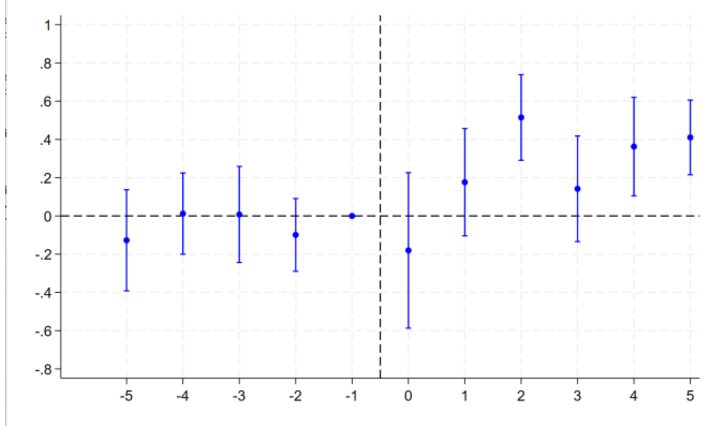
(c) log Days (Buyer)



(d) log Price



(e) Rating (Buyer)



(f) Rating (Seller)

Rollout DiD Results: Overall Effects

Main patterns: sale probability ↑, time-to-transaction ↓, prices ↑, ratings ↑ (in paper).

	Sold$<$ 3m	log Days (S)	log Days (B)	log Price
Post$\times$Ratio_tran	0.4215***	-0.4434***	-0.2484***	0.1005***
	(0.080)	(0.145)	(0.047)	(0.029)
Effect of +10pp exposure	+4.2 pp	-4.3%	-2.5%	+1.0%
Control mean	0.546	–	–	–
N	267,882	231,680	231,680	231,680
Controls	Yes	Yes	Yes	Yes
City$\times$Month FE	Yes	Yes	Yes	Yes
Neighborhood FE	Yes	Yes	Yes	Yes

Notes: SE clustered at the **district** level.

Decomposition Setup: Own-side vs Cross-side Effects

- Replace overall exposure with buyer-side and seller-side exposure:

$$\text{Post} \times \text{Ratio\_buyer}_d, \quad \text{Post} \times \text{Ratio\_seller}_d.$$

- Goal: separate buyer- vs seller-side exposure effects on buyer and seller outcomes.

Conceptual object (reduced-form response matrix):

$$M = \begin{pmatrix} \dfrac{\partial \text{Y\_seller}}{\partial \text{Ratio\_seller}} & \dfrac{\partial \text{Y\_seller}}{\partial \text{Ratio\_buyer}} \\ \dfrac{\partial \text{Y\_buyer}}{\partial \text{Ratio\_seller}} & \dfrac{\partial \text{Y\_buyer}}{\partial \text{Ratio\_buyer}} \end{pmatrix}$$

diagonal = own-side, off-diagonal = cross-side.

Decomposition Results: Cross-side Effects & Price Loading

- **Speed outcomes:** both buyer and seller exposure matter for both sides.
- **Prices:** increase loads primarily on buyer-side exposure; seller-side exposure ≈ 0.
- **Ratings:** improve with both own-side and cross-side patterns (see paper).

	Sold$<$ 3m	log Days (S)	log Days (B)	log Price
Post$\times$Ratio_buyer	0.1744*	-0.2376**	-0.1411**	0.1152***
Post$\times$Ratio_seller	0.4117***	-0.4877**	-0.2550***	-0.0005
Effect +10pp buyer exp	+1.7 pp	-2.3%	-1.4%	+1.2%
Effect +10pp seller exp	+4.1 pp	-4.8%	-2.5%	0.0%
N	267,882	231,680	231,680	231,680
Controls	Yes	Yes	Yes	Yes
City$\times$Month FE	Yes	Yes	Yes	Yes
Neighborhood FE	Yes	Yes	Yes	Yes

Notes: SE clustered at the **district** level.

Robustness Checks

- **Exclusion and concurrent changes:**
  - Add **Post** $\times$ **covariates** (district conditions & property controls).
  - **Digitization confound:** app penetration is smooth (no break at rollout).
- **Alternative specifications:**
  - Exposure-group dummies (Callaway et al., 2024).
  - Alt exposure: post district-level AI-usage density (overall, buyer, seller).
- **Inference:** cluster SEs at **city** level.
- **Spillovers:** drop neighborhoods that straddle district boundaries.
- **Composition:** no meaningful shifts in listing composition around rollout.
- **Placebos:** outcomes the copilot should not affect show no systematic effects.

Process Evidence (Mechanisms Consistent with Reduced Frictions)

Buyer-side tools (recommendations & reply scripts)

- **Search/coordination:** viewings per transaction ↓
- **Buyer feedback:** recommendation / communication / trust labels ↑

Seller-side tools (pricing guidance & listing text)

- **Price discovery:** adjustment frequency ↑, magnitude ↓
- **Seller feedback:** pricing / selling-point labels ↑

	Buyer-side process outcomes			Seller-side process outcomes		
	Viewings (search effort)	Recomm. optimal	Comm. ineff.	Adj. times (weekly)	Adj. magn. (abs)	Pricing optimal
Post×Ratio_buyer	-0.3548^{**}	$+0.2324^{**}$	-0.0608^{***}	$+0.0204$	$+0.2791$	$+0.0041$
	(0.163)	(0.109)	(0.016)	(0.027)	(0.204)	(0.070)
Post×Ratio_seller	$+0.3094$	$+0.2587^{**}$	-0.0129	$+0.0820^{***}$	-0.7933^{***}	$+0.3331^{***}$
	(0.190)	(0.101)	(0.017)	(0.031)	(0.244)	(0.058)

Heterogeneous Treatment Effect

- Are the positive cross-side effects more pronounced for less-experienced agents?

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

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

Heterogeneous Treatment Effect

- Are the positive cross-side effects more pronounced for less-performing agents?

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

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

Heterogeneous Treatment Effect

- Are the positive effects on main outcomes moderated by market thickness (listings)?

Table A14: Heterogeneity in the Effect of AI Adoption by Market Thickness

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

Conclusion

- **What we study:** an agent-facing AI copilot for real-estate agents on a leading Chinese used-housing platform (active only in in-app chat).
- **Main effects & cross-side effects:** the market clears faster, and exposure on one side speeds outcomes on the other (two-sided spillovers); prices rise mainly with buyer-side exposure.
- **Interpretation:** process evidence is more consistent with reduced search/coordination frictions than with a purely redistributive shift in value.
- **Learning:** Evaluating agent tools require separating **own**- and **cross-side** effects. Which side is augmented can affect liquidity vs. price effects. In the long run, incidence affects participation, so platforms care about balanced value capture.
- **Limitations:** bundled tool; no usage data; tool mix/adoption and institutions may affect external validity (e.g., MLS-style environments).

Thank you!