Leveling the Playing Field: the Effect of Generative AI on Small and Medium-Sized Firms

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Abstract

This paper examines whether platform-enabled AI tools can enable small firms to narrow the capability gap with larger incumbents in digital marketplaces. We study the staggered adoption of an AI tool — automated content generation and data analytics — launched in April 2024 on a leading Chinese e-commerce platform. Leveraging a proprietary firm-level panel of over 4.9 million firm-month observations from October 2023 to July 2025, we combine propensity score matching with difference-in-differences estimation across twelve adoption cohorts. We find that AI adoption increases average sales by 69.9%, driven primarily by a 63.2% rise in order volume, with broad improvements across discoverability, quality, and innovation. These gains are sharply heterogeneous by firm size: bottom-quartile firms experience 75.8% sales growth — nearly four times the 19.9% gain of top-quartile firms — with disproportionate improvements in other dimensions of firm performance. Mechanism analyses reveal that AI reduces labor costs and alleviates information asymmetries, with both effects concentrated among smaller firms. Additional evidence suggests that AI adoption expands market demand rather than merely reallocating sales across firms. Results are robust to instrumental variable, staggered DiD, and synthetic DiD approaches. Overall, the evidence suggests that when made accessible with low adoption costs, AI can narrow pre-existing capability gaps rather than exacerbate them, fostering upward mobility among small firms and enhancing market dynamism.

Keywords: Artificial intelligence, firm performance, innovation, upward mobility, digital divide

JEL Codes: L81, L86, O33, D22, D24

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1. Introduction

The rapid diffusion of artificial intelligence (AI) has reignited longstanding debates over whether new technologies exacerbate or reduce economic inequality. On one hand, AI may exhibit increasing returns to scale and confer data advantages that potentially reinforce incumbent market positions and raise barriers to entry (Bajgar et al. 2021, McElheran et al. 2025). On the other hand, AI tools that lower fixed costs for key business features, such as data analysis, customer service, and content creation, could disproportionately benefit resource-constrained small firms, enabling them to compete more effectively with larger incumbents (Damioli et al. 2021). Which force dominates is ultimately an empirical question, yet causal evidence on how AI adoption affects firms of different sizes remains limited.

This paper provides such evidence by studying the staggered adoption of a platform-enabled AI tool on a leading Chinese e-commerce platform. Launched in April 2024, the tool integrates two core features: automated content generation for product listings (text, images, and videos) and data analytics (market insights, performance metrics, and new-product guidance). Adoption costs were negligible, and the tool was seamlessly integrated into the existing platform workflows, distinguishing it from earlier digital technologies that required substantial fixed investments and complementary organizational capabilities (Bresnahan et al. 2002, Brynjolfsson and Hitt 2003).

Our analysis leverages a proprietary firm-level panel covering over 4.9 million firm-month observations from October 2023 to July 2025. The dataset integrates detailed information on AI usage logs, page views, transaction volume and value, operational performance indicators (including customer service quality and delivery efficiency), and firm characteristics. This rich structure allows us to track dynamic changes in firm behavior and outcomes before and after AI adoption, and to examine the mechanisms linking AI to firm performance. Identification combines propensity score matching with difference-in-differences estimation. We construct twelve adoption cohorts, each comprising sellers who first adopt the tool within a specific calendar month spanning from July 2024 to June 2025. For each treated firm, we match it to a never-adopting control firm using pre-treatment characteristics, including firm age, product category, store type, sales, and product count. The final matched sample includes 148,770 treated firms and 77,347 distinct controls. Event-study plots confirm parallel pre-treatment trends. To assess robustness, we supplement the baseline analysis with a shift–share instrumental variable approach (instrumenting AI adoption with a firm's pre-AI adoption exposure interacted with the category-level AI adoption rate), staggered differences-in-differences (DiD), and synthetic DiD methods.[1] All approaches yield consistent results.

[1]We define adoption exposure as the interaction between a firm's pre-adoption frequency of product modifications and the province-level digitalization index.

We find that AI adoption increases average sales by 69.9%, primarily through a 63.2% increase in order volume. Beyond sales, AI adoption enhances firm performance in several ways. First, discoverability improves: page views increase by 63.6% and new visitors by 47.5%. Second, quality improves: negative review rates decline by 4%, 24-hour on-time pickup rates rise by 2.3%, delivery times shorten by 2.3%, and firm-liable disputes decrease by 36%. Third, innovation accelerates: firms introduce 27.3% more new products each month, expand into 16.5% more product categories, and generate substantial new-product sales.

These effects are highly heterogeneous by firm size. Firms in the bottom quartile of pre-treatment sales experience 75.8% sales growth, with gains in both order volume and average order value (revenue per transaction). In contrast, top-quartile firms grow by only 19.9%, driven primarily by volume expansion and accompanied by a decline in average order value. Performance improvement in discoverability, quality, and innovation is similarly concentrated among smaller firms. Together, these findings provide evidence that platform-enabled AI tools can function as an equalizing force, enabling small firms to access capabilities previously attainable only to large firms.

We further examine the underlying mechanisms through which AI empowers firms and explore why smaller firms benefit disproportionately. First, AI reduces operating costs. AI adoption significantly reduces average human customer service time per order, with larger reductions among smaller firms. In addition, firms located in high-labor-cost regions experience larger sales gains after adoption, especially smaller firms, consistent with AI substituting for labor-intensive operational tasks. Second, AI alleviates information asymmetries. AI adoption improves firms' alignment with category-level price trends, expands product title length, increases pickup timeliness, and reduces delivery time. These outcomes suggest that AI helps firms process market price information, demand information, and operational information. Moreover, firms in categories with higher baseline refund rates- our proxy for greater information frictions—experience larger gains from AI adoption, particularly among small and medium-sized firms.

We also examine whether the estimated effects reflect market expansion or competitive reallocation. This distinction is important because AI adoption by treated firms could, in principle, increase their sales by drawing demand away from non-adopters. Several results suggest that this is not the primary explanation. At the category level, markets with higher baseline information asymmetry experience larger increases in sales, new sellers, and new products after AI diffusion, while market concentration declines. At the firm level, we find no evidence that the treatment effects are stronger in categories with higher large-firm AI adoption rates or higher overall AI adoption rates. Moreover, the estimated effects are larger in more concentrated markets, which is inconsistent with a simple business-stealing interpretation. These findings suggest that AI expands market activity and supports

small-firm upward mobility rather than merely reallocating demand among existing sellers.

Literature Review We contribute to the literature on the development of small and medium-sized enterprises (SMEs). SMEs play a central role in economic growth (Beck et al. 2005, Ayyagari et al. 2007), yet their development has long been constrained by resource limitations and organizational capacity gaps. The rise of the digital economy has partially alleviated these constraints, but it has also introduced new information frictions and digital divides (Arendt 2008, Tadelis 2016, Goldfarb and Tucker 2019). Prior research shows that the Internet, information technology and automation can improve the SME performance, for instance, by increasing credit availability (Petersen and Rajan 2002), lowering information cost and enhancing data-driven decision making (Bar-Gill et al. 2024), and promoting exports (Kim et al. 2020). However, these technologies often require substantial fixed costs, and their effectiveness depends on complementary capabilities such as organizational adaptation and sound management practices (Bresnahan et al. 2002, Bloom et al. 2012). As a result, larger firms with better human capital and organizational advantages tend to benefit more, leaving the digital divide for SMEs largely intact (Brynjolfsson and Hitt 2003, Brynjolfsson et al. 2021).

In contrast, our paper examines a platform-enabled AI tool that differs from prior technologies along several key dimensions. With negligible adoption costs, seamless integration into platform workflows, and narrowly scoped, task-specific features, the tool is both affordable and readily accessible to SMEs, and is therefore well-positioned to generate greater benefits for smaller firms. Our findings provide novel evidence that AI technologies (when made accessible) can mitigate the persistent digital and capability divides faced by small firms.

Our study also contributes to the growing literature on AI adoption and firm dynamics. Theoretical research suggests that AI's effect on productivity may follow a "J-curve," with short-term adjustment costs causing performance fluctuations before gains materialize in the long-run (Tambe et al. 2020, Brynjolfsson et al. 2021, Bäck et al. 2022). Empirical evidence generally supports the positive effects of AI on firm productivity and value, drawing on surveys of AI adoption (Czarnitzki et al. 2023), measures of human capital with AI expertise or AI exposure (Alekseeva et al. 2021, Eisfeldt et al. 2023), AI-related patents (Damioli et al. 2021, da Silva Marioni et al. 2024), or the exogenous release time of ChatGPT (Cai et al. 2025). Mechanisms studied in this literature include labor substitution (McElheran et al. 2025), innovation incentives (Babina et al. 2024, da Silva Marioni et al. 2024), and complementarity with external technological environments (Zeng et al. 2025).

Relative to the growing number of studies on AI and labor productivity, firm-level empirical research remains nascent, limited by data availability and relatively low AI adoption rates. An exception is Goldberg and Lam (2025), who find that generative AI assistants positively affect

image production and sales on product design platforms. However, their analysis is limited to a single industry and focuses primarily on changes in market structure rather than firm-level capability accumulation.

Our paper advances this literature in two important ways. First, prior work has largely relied on indirect proxies for AI adoption, such as patent counts, skill measures, or aggregate exposure indices. We leverage direct, high-frequency, and large scale observational data on AI tool usage at the firm level drawn from a large e-commerce platform spanning across all product categories. This enables more precise identification of causal effects across a broad and representative sample of firms. Second, we go beyond aggregate sales or productivity outcomes to provide a comprehensive assessment of AI-driven capability accumulation across multiple dimensions, including discoverability, quality, and innovation. We further uncover three mechanisms through which AI differentially empowers small firms: cost reduction, alleviation of information asymmetries, and skill acquisition.

Lastly, our paper speaks to the debate over whether AI exacerbates performance divergence or narrows gaps across firms and labors. On the one hand, due to high fixed costs, economies of scale, and lagged returns, firms with advantages in capital, data, and technological accumulation tend to benefit earlier and more fully, raising barriers to entry and increasing industry concentration (Bajgar et al. 2021, McElheran et al. 2025, Hagiu and Wright 2025). Evidence suggests that after AI diffusion, productivity gaps between leading and lagging firms often widen, with large firms and early adopters benefiting more (Bäck et al. 2022, Calvino and Fontanelli 2023, Czarnitzki et al. 2023, Igna and Venturini 2023, da Silva Marioni et al. 2024). Moreoever, lagging firms or less-skilled labors may be unable to effectively interpret and implement AI recommendations due to limited knowledge, skills, or resources, potentially undermining performance (Brynjolfsson et al. 2021, Dell'Acqua et al. 2023, Otis et al. 2024).

On the other hand, our paper provides evidence that by lowering barriers to advanced technologies and management capabilities. AI can help SMEs or technologically lagging firms acquire knowledge, accelerate capability accumulation, and achieve higher marginal returns, thus narrowing gaps with frontier firms (Damioli et al. 2021, da Silva Marioni et al. 2024, Cai et al. 2025). The platform-enabled AI tools in our context facilitate upward mobility among smaller firms, narrowing capability gaps and fostering more competitive and market outcomes.

The remainder of the paper proceeds as follows. Section 2 describes the institutional setting. Section 3 presents data and empirical strategy. Section 4 reports main results. Section 5 examines heterogeneity and upward mobility. Section 6 explores mechanisms. Section 7 discusses market expansion, spillovers, and heterogeneity in AI usage. Section 8 provides robustness checks, and Section 9 concludes.

2. Institutional Background

E-commerce operations require the coordination of multiple, highly fragmented tasks, including content production, product listing, customer service, data analysis, and strategic decision-making. Effective and seamless execution of these tasks requires substantial investments in labor and capital, as well as significant experience in online management and operations. These requirements pose particular challenges for small and medium-sized firms, who often face resource constraints and limited managerial capacity.

To address these challenges, the platform in this study launched an AI-assisted tool for firms in April 2024, with the aim of reducing operating costs and improving managerial efficiency (See Figure 1). Hosting billions of listings, millions of firms, and hundreds of millions of buyers, the marketplace generates tens of millions of daily transactions and billions in Gross Merchandise Volume (GMV). This massive scale provides a rich and highly representative empirical setting for our analysis.

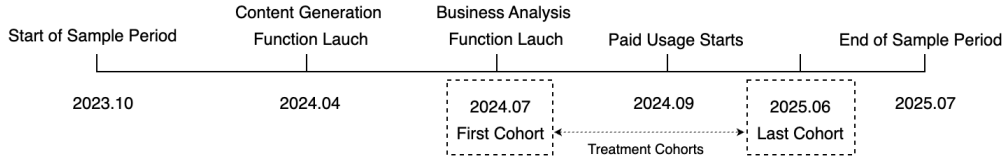


Figure 1: Timeline of AI launching

The AI tool comprises two core features: content generation and data analytics. It was made freely available to all firms on the platform prior to September 2024, after which it transitioned to a subscription-based pricing scheme under which the first month is free and continued access is priced at RMB 99 (roughly $14) per month.

The content generation feature, launched in April 2024, supports the automated creation and editing of texts, images, and videos for online product listings. To illustrate how AI enhances content generation relative to the traditional human-driven process, consider the production of product images featuring real models. Under the conventional workflow, this process typically involves model selection, studio or on-location rental, physical photo shoots, and post-production editing, requiring approximately three to seven days and costing about RMB 80 per image. By contrast, the AI tool enables firms to generate high-quality model images in roughly 20 seconds at negligible costs. Firms simply upload a few organic product photos taken with a smartphone, and the module automatically handles key visual elements of product presentation, including fitting products to appropriate models, background replacement, high-resolution image restoration, and even virtual try-on for footwear. Video production is similarly resource-intensive under traditional methods: short promotional videos commonly require one to seven days to produce and cost around RMB

300 per video. In contrast, the AI tool allows firms to generate marketing videos within three to five minutes using a single product image, substantially reducing both time and monetary inputs. In addition, the copywriting feature generates product titles, marketing copy, and video scripts that reflect prevailing product selling points and market trends, providing low-cost creative support. Taken together, the content generation module reduces cost pressures across labor, time, and capital in routine operational activities such as model selection, photo shoots, and post-production editing.

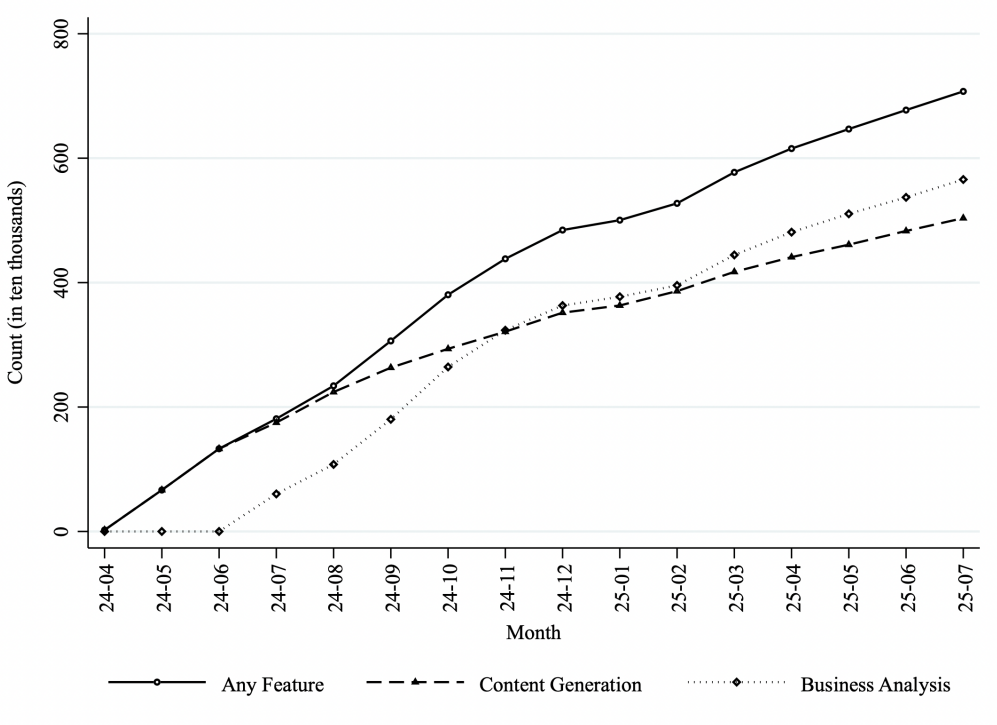
The data analytics feature was introduced in July 2024 and spans six modules: (i) operational knowledge, which synthesizes key online operational know-how, including platform rules and tool usage guidance; (ii) data analysis, providing data-driven insights such as seller performance metrics and market trend highlights; (iii) marketing, supporting intelligent new-product outreach and promotional activities; (iv) product management, offering guidance on product quality, pricing, and diagnostics; (v) customer service, including automated responses and delayed-response alerts; and (iv) logistics service, facilitating management through features such as pickup delay alerts and shipment updates. Table 1 provides a detailed description of these components. Drawing on the platform's accumulated data on consumer behavior and market dynamics, this feature provides market-relevant business insights and actionable managerial guidance to support seller decision-making.

Table 1: Features and Module Description

Modules	**Specific Description**
Feature 1: The content generation	
Generation	Texts (product titles, marketing copies, and video scripts), product images, product videos
Editing	Product image editing, product video editing
Feature 2: The data analytics	
Operational Knowledge	Platform rules, tool usage guidance, store risk alerts, order management, membership management, live-streaming assistant, financial management, operations assistant
Data Analytics	Performance metric queries and interpretation, market trend and selling-point analysis, competitor store data analysis, profit analysis
Marketing	Intelligent new-product outreach, marketing assistant, promotion assistant
Product Management	High-quality or low-price supply detection, product optimization, product diagnostics, product quality scoring
Customer Service	Customer service assistant, automated replies, delayed-response alerts
Logistics Service	Pickup delay alerts, logistics update notifications, logistics assistant

As of July 2025, approximately 7 million firms had used at least one AI feature provided by the platform. Among them, about 20% firms used only the content generation feature, roughly 30% used only the data analytics feature, and nearly half used both features. Figure 2 presents the cumulative count of adopters of the tool and its two features.

Figure 2: Cumulative Count of Adopters



3. Data and Empirical Strategy

Our study exploits granular data from a world-leading e-commerce platform. We leverage the introduction of a newly launched AI tool on the platform and identify the causal effects of AI tool adoption on firm performance using a combination of a matching method and a difference-in-differences approach.

3.1 Data Description

We utilize a proprietary dataset from a leading global e-commerce platform. The dataset used in this study spans from October 2023 to July 2025 and integrates four pieces of information. First, data on AI tool usage records firms' actual use of different AI features over time. Second, monthly exposure and transaction data including page views, visitor counts, new visitor counts, gross merchandise value, order volume, number of items sold, number of new launches, and the number of buyers. Third, monthly operational indicators cover refund outcomes, product negative review rates, fulfillment and logistics performance, customer service responsiveness, and firm-responsibility dispute measures. Fourth, firm characteristics include firm tenure, geographic location, primary product category, and store type.

This high-frequency, long-span firm-level panel data allows us to systematically track the dynamic

changes in firm behavior and performance before and after AI tool adoption. It also facilitates the exploration of underlying mechanisms, further enabling us to identify how AI technologies transmit their effects to final performance outcomes by shaping specific operational decisions, thereby providing direct evidence on the microeconomic impact of AI as a general-purpose technology.

3.2 Sample Selection and Summary Statistics

While the platform hosts tens of millions of firms, frequent entry and exit introduce significant noise in data, complicating the measurement of treatment effects. To ensure empirical tractability, comply with platform privacy guidelines, and maintain focus on our core research question, we construct our estimation sample through a three-step procedure. First, we restrict the sample to consistently active firms, defined as those completing at least one transaction in every month between October 2023 and July 2025, to mitigate noise stemming from firm turnover and the presence of opportunistic, short-lived operations. Second, we exclude large firms with annual sales exceeding RMB 5 million. Because these top-tier firms are few in number and exhibit disproportionately high AI adoption rates, finding appropriate matched controls within this group is empirically challenging. Moreover, they often have access to alternative AI tools and resources beyond the platform's AI offerings, which could confound the estimated effects. Thus, we focus exclusively on firms below the RMB 5 million threshold. The third step entails matching treated firms with suitable controls. We detail the process below.

We define the treatment group as firms who adopt both AI features. To ensure a precisely defined intervention point, we require the adoption of these two features to occur within a one-month window. The control group comprises firms who do not use either AI feature at any time during the sample period. To isolate the impact of AI adoption and mitigate selection bias stemming from observable differences, we match treated firms with untreated controls. Specifically, we estimate propensity scores using a comprehensive set of pre-adoption baseline attributes and performance variables, including firm age, primary product category, store type, sales volume, and product count.

Due to the staggered nature of adoption, we employ a cohort-specific matching procedure following Cengiz et al. (2018). First, we construct 12 distinct treatment cohorts, each comprising firms who adopted the AI tool in a specific month between July 2024 and June 2025. For each cohort, we then implement 1:1 nearest-neighbor caliper matching on a month-by-month basis. Specifically, starting with the initial cohort (July 2024), we match adopters with control firms drawn from a pool of firms that never adopted the tool during the sample period. We retain these matched pairs and repeat the procedure for each subsequent adoption month. We perform matching with replacement across cohorts, implying that a single firm from the control group may be matched with treatment

firms in multiple adoption months. The final matched sample includes 148,770 treated firms and 77,347 distinct control firms.[2]

Summary statistics are reported in Table 2. An event study using the matched sample demonstrates that pre-treatment sales trends are parallel between the treatment and control groups.

Table 2: Summary Statistics

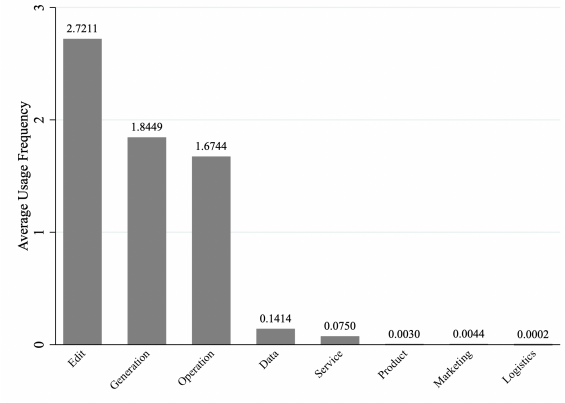
Variable	Mean	Std	P5	P50	P95
Sales	8.08	1.65	5.38	8.18	10.76
Orders	3.69	1.49	1.39	3.56	6.31
Price	4.46	1.28	2.61	4.40	6.85
Firm Page Views	7.59	1.69	4.84	7.57	10.41
Firm Total Visitors	6.70	1.67	3.97	6.68	9.46
Product Page Views	7.47	1.71	4.68	7.45	10.30
Firm New Visitors	6.61	1.69	3.85	6.58	9.39
New Customer Number	3.14	1.59	0.69	3.00	5.88
New Customer Sales	7.25	2.28	3.33	7.50	10.36
%New Customer Sales	0.63	0.32	0.018	0.72	1.00
Refund Rate	0.055	0.10	0	0.017	0.24
Product Negative Review Rate	0.025	0.15	0	0	0.021
Firm-Liability Dispute Rate	0.0072	0.055	0	0	0.05
New Category Number	0.14	0.52	0	0	1.10
New Product Number	0.22	0.80	0	0	1.79
New Product Sales	2.31	3.26	0	0	8.82
Average Customer Service Time Per Order	1.16	0.83	0.13	0.98	2.76
Firm Price Change	0.73	0.45	0	1	1
Average Title Length	0.98	1.55	0	0	3.55
Average Delivery Time	4.15	0.31	3.72	4.11	4.66
24h Pickup Ontime Rate	0.86	0.20	0.5	0.97	1

Notes: All non-ratio continuous variables in the table have been transformed using the natural logarithm. The same log-transformed variables are used in both the regression analyses and descriptive statistics, while ratio variables and dummy variables remain in their original values. Ratio variables include Return Rate, 24h Pickup Ontime Rate,Product Bad Reviews Rate, Firm Liability Rate in Disputes,New Customer CVR and %New Customer Sales.

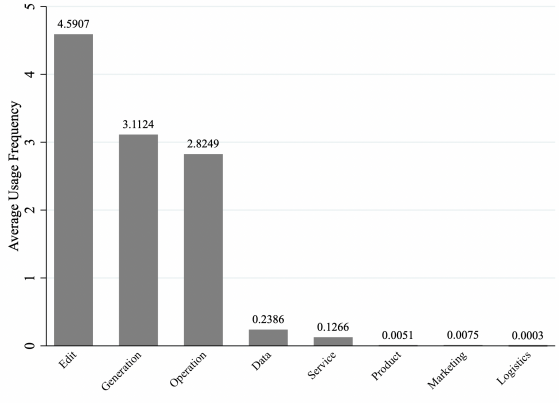
Figure 3 presents the average monthly usage frequency of each module by adopting firms. Panel A calculates the mean over the entire period from adoption to the end of the sample (including zero-usage months), whereas Panel B calculates the mean only over active months with positive usage.

[2]There are fewer distinct control group firms compared to treatment group firms because one control group firm may be matched with multiple treatment group firms, both in different cohorts and the same cohorts. We use weighted regression in our analysis.

Figure 3: Monthly Usage



(a) Monthly Usage(including zero-usage months)



(b) Monthly Usage(over active months)

3.3 Empirical Strategy

To identify the causal effect of AI tool adoption on firm performance, our study employs a combined Propensity Score Matching and Difference-in-Differences (PSM-DiD) approach. The Difference-in-Differences (DiD) model is specified as follows:

$$y_{it} = \beta \times \text{Treat}_i \times \text{Post}_{c(i)t} + \mu_i + \phi_{c(i)} + \tau_t + \varepsilon_{it} \tag{1}$$

where y_{it} denotes outcomes of interest. Treat_i is a binary indicator that equals 1 if a firm adopted AI during the sample period, and 0 otherwise. $\text{Post}_{c(i)t}$ equals 1 if the timestamp is the month of a firm's first AI adoption or any subsequent month. μ_i, $\phi_{c(i)}$, and τ_t denote firm fixed effects, cohort fixed effects, and time fixed effects, respectively. ε_{it} stands for a random error term. β is the coefficient of interest that identifies the policy effects on AI-adopting firms. The standard errors are all clustered in the category level.

4. The Impact of AI on Firm Performance

In this section, we first estimate the effect of AI adoption on firm sales performance, focusing on sales revenue, the number of orders, and average order value. We then examine how AI adoption affects firm performance in multiple ways, including product discoverability, product quality, operational quality, and innovation.

4.1 Sales Performance

Table 3 shows that AI has a substantial positive effect on firm sales performance, with average sales increasing by 69.9% and the number of orders rising by 63.2%[3]. While the price shows no significant change, the substantial growth in both sales revenue and order volume highlights that the AI tool has enabled firms to capture more transaction opportunities and attract additional consumer purchases.

Table 3: Firm Performance

VARIABLES	(1) Sales	(2) Orders	(3) Price
Treat × Post	0.530***	0.490***	0.00901
	(0.0314)	(0.0298)	(0.00774)
Time FE	✓	✓	✓
Cohort FE	✓	✓	✓
Firm FE	✓	✓	✓
Observations	4,974,574	4,974,574	4,974,574
R-squared	0.662	0.709	0.817

Notes: Robust standard errors in parentheses and standard errors are clustered at the categroy level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

4.2 Multidimensional Performance

We further investigate how AI adoption enhances firm performance across multiple dimensions. The results indicate that AI strengthens core business performance by increasing firms' discoverability, improving product and operational quality, and facilitating supply-side innovation, thereby driving significant improvements in performance.

4.2.1 Discoverability

To assess whether AI tools enhance firm discoverability, we estimate the effect of AI adoption on exposure-related metrics. Table 4 documents significant increases in firm page views, product page views, total visitors, and new visitors following AI adoption. For example, AI adoption increases firm page views by approximately 63.6% on average, with effects of similar magnitude for the other metrics. These results show that AI adoption significantly improves firm visibility and customer reach, especially leading to a marked increase in new visitors. This exposure enhancement effect

[3]Since the dependent variables are expressed in logarithms, we transform coefficients into percentage changes using $100 \times (e^{\beta} - 1)$. For instance, the 69.9 percent reported in column (1) of Table 1 corresponds to $100 \times (e^{0.53} - 1)$.

likely arises from AI-driven reduction in the cost of content generation and editing, which enables firms to expand the volume of listings that are searchable and matchable on the platform, as well as from AI-induced optimization in product textual and visual information, which allows firms to improve the quality of listings and their effectiveness within the platform matching system.

In addition, Table 5 indicates that the AI tool shows strong market expansion effect. It significantly increases the number of new customers, generating substantial growth in new-customer spending and raising the share of sales attributable to new customers. Taken together, the evidence suggests that AI not only strengthens engagement with existing users but also expands demand by attracting new customers. Moreover, we observe a significant increase in conversion rates among new customers, providing further evidence of the effective enhancement of discoverability. Overall, sales growth is primarily driven by new customers, and improved discoverability represents a central mechanism through which AI enhances firm performance.

Table 4: Firm Discoverability

	(1)	(2)	(3)	(4)
VARIABLES	Firm Page Views	Firm Total Visitors	Product Page Views	Firm New Visitors
Treat × Post	0.492***	0.475***	0.497***	0.475***
	(0.0296)	(0.0288)	(0.0309)	(0.0296)
Time FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Observations	4,974,574	4,974,574	4,974,574	4,974,574
R-squared	0.751	0.747	0.746	0.745

Notes: Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

4.2.2 Quality

We use three measures to capture changes in firm quality. Column (1) of Table 6 reports the refund rate, a composite measure that reflects overall firm performance in terms of product quality, fulfillment, and service. It is defined as the ratio of monthly refunded orders to completed transactions at the firm level. The results show that, although the adoption of AI tools significantly increases transaction volume, it does not lead to an increase in the refund rate. This pattern suggests that firms are able to scale up without a deterioration in service capacity or product quality.

To better capture evidence of quality improvement, we categorize refunds based on the initiating party into consumer-responsible, firm-responsible, and mutually agreement (Table 7, columns (1)–(3)). The estimates indicate that AI adoption significantly reduces the proportion of refunds

Table 5: Expansion Effect

	(1)	(2)	(3)	(4)
		New Customer		
VARIABLES	Number	Sales	%Sales	CVR
Treat × Post	0.516***	0.715***	0.0393***	0.00494***
	(0.0214)	(0.0245)	(0.00244)	(0.000595)
Time FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Observations	4,974,574	4,974,574	4,974,574	4,974,574
R-squared	0.705	0.579	0.597	0.526

Notes: Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

attributable to firms. Decomposing firm-responsible refunds into service, product, and logistics quality (Table 7, columns (4)-(6)), we find that none increase significantly, while service-related refunds decline markedly, providing additional evidence that AI improves operational and service quality. Notably, consumer-responsible refunds rise following AI adoption, likely reflecting natural market frictions: increased exposure attracts more new consumers who are less familiar with individual firms, increasing the likelihood of preference–product mismatches, while not indicating a decline in firm quality.

Columns (2) and (3) of Table 6 provide more evidence along the dimensions of product quality and operational service quality. Column (2) examines the negative review rate, defined as the share of negative reviews among all customer reviews. We find a significant decline in this measure following AI adoption, indicating improvements in product quality or product–consumer matching. Column (3) reports the firm-liability dispute rate, defined as the share of disputes in which the platform assigns responsibility to the firm. The reduction in this measure implies that, conditional on transaction volume, firms experience fewer failures in fulfillment, communication, and service, consistent with an improvement in operational quality.

Taken together, the evidence measures suggests that AI adoption not only expands transaction scale but is also associated with improvements in observable quality outcomes. These findings indicate that the impact of AI on firm performance extends beyond demand-side traffic acquisition and operates through meaningful quality improvements on the supply side.

Table 6: Quality

	(1)	(2)	(3)
VARIABLES	Refund Rate	Product Negative Review Rate	Firm-Liability Dispute Rate
Treat × Post	0.000875	−0.0390***	−0.00334***
	(0.000631)	(0.00327)	(0.000387)
Time FE	✓	✓	✓
Cohort FE	✓	✓	✓
Seller FE	✓	✓	✓
Observations	4,974,574	4,974,574	4,974,574
R-squared	0.380	0.503	0.140

Notes: Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 7: Different Refund Reasons(%)

	(1)	(2)	(3)	(4)	(5)	(6)
	Different Reasons			Firm-responsible Reason		
VARIABLES	Consumer	Firm	Mutual Agreement	Service	Product	Logistics
Treat × Post	0.0342***	−0.00786***	−0.00524*	−0.00441***	−0.00274	−0.000711
	(0.00453)	(0.00239)	(0.00264)	(0.00153)	(0.00164)	(0.00145)
Time FE	✓	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Observations	3,470,528	3,470,528	3,470,528	3,470,528	3,470,528	3,470,528
R-squared	0.288	0.232	0.375	0.169	0.178	0.212

Notes: Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

4.2.3 Innovation

Finally, we examine whether AI tools positively influence firms' innovative activities. Innovation is a key driver of long-term competitive advantage in dynamic markets and a critical micro-level foundation for improving market efficiency and consumer welfare. We focus on two measures to capture firm innovation activity: the number of new products introduced by a firm each month and the number of product categories covered by these new offerings. We further evaluate the effectiveness

of these innovations by examining the sales performance of the newly introduced products.

Table 8 shows that AI adoption increases the average monthly number of new products by approximately 27.3% and expands the range of product categories spanned by these new offerings by 16.5%, thereby facilitating supply-side innovation. The substantial increase in sales of new products further indicates that AI-driven innovation generates tangible market value, thereby promoting the growth of effective innovation. The AI-driven increase in innovation not only underscores its multidimensional impact on firm performance but also highlights the broader role of digital tools in stimulating entrepreneurial creativity, fostering industrial upgrading, and enhancing market competitiveness.

Table 8: Supply-side Innovation

	(1)	(2)	(3)
VARIABLES	New Product Number	New Category Number	New Product Sales
Treat × Post	0.242^{***}	0.153^{***}	1.094^{***}
	(0.0250)	(0.0134)	(0.0367)
Time FE	✓	✓	✓
Cohort FE	✓	✓	✓
Firm FE	✓	✓	✓
Observations	4,974,574	4,974,574	4,974,574
R-squared	0.355	0.343	0.514

Notes: Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

In sum, our evidence shows that AI adoption benefits firms not only by boosting short-term sales but also by systematically strengthening their multidimensional capabilities for sustainable growth, particularly enhancing quality and innovation incentives.

5. Upward Mobility

A central question of interest is whether AI adoption enhances market dynamism by empowering smaller firms or instead entrenches the existing advantages of incumbents. In this section, we focus on whether AI facilitates the upward mobility of small and micro firms, thereby contributing to small-firm growth and market dynamism. To investigate this, we analyze heterogeneous effects of AI adoption using subgroup regressions, grouping firms into quartiles according to their pre-treatment annual sales.

5.1 Size Heterogeneity in Sales Performance

As shown in Table 9, the positive effects of AI on sales decline monotonically with firm size, with the largest gains accruing to firms in the bottom quartile. These results suggest that the AI tool is generating greater benefits for smaller firms.

Furthermore, bottom-quartile firms exhibit a dual effect of both scale expansion and value enhancement. AI adoption significantly increases both order volume and average order value for the bottom-quartile firms. This pattern is consistent with AI improving the efficiency of information transmission and product presentation, allowing small firms to expand transaction volume while simultaneously increasing value per order.

By contrast, growth among top-quartile firms is driven primarily by scale effects. Although AI adoption significantly raises order volume, it is associated with a decline in price. This suggests that AI helps the larger firms to expand market coverage and reach a broader, more price-sensitive customer base. Correspondingly, growth among these firms is primarily driven by higher transaction frequency, accompanied by a decline in average order value. It is worth noting that the increase in sales revenue is lower than that for order volume, providing further evidence for this scale-dominated growth pattern.

5.2 Size Heterogeneity in Multidimensional Performance

Furthermore, we examine the heterogeneous impact of AI adoption on firms' multidimensional performance. The results in Table 10 show that improvements in discoverability, quality enhancements, and innovation incentives are disproportionate and most pronounced among firms in the bottom quartile, with effects that are persistent over time. By contrast, these effects are relatively weaker and more short-lived for top-tier firms.

These findings suggest that platform-enabled AI tools can serve as an equalizing force in digital marketplaces by enabling small firms to access advanced AI-driven capabilities, such as data analytics, personalized content generation, and automated operations, at relatively low cost. These capabilities were previously concentrated among large firms. This form of technological empowerment not only improves the performance of lower-tier firms but also supports capability accumulation, thereby facilitating their dynamic upward mobility and contributing to a more balanced competitive landscape.

Table 9: Heterogeneity in Sales Performance

VARIABLES	Panel A: Bottom and Lower-Middle					
	Bottom			Lower-Middle		
	Sales	Orders	Price	Sales	Orders	Price
Treat × Post	0.758***	0.647***	0.0599***	0.434***	0.423***	−0.0146
	(0.0299)	(0.0280)	(0.0149)	(0.0238)	(0.0233)	(0.00956)
Time FE	✓	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Observations	1,332,364	1,332,364	1,332,364	1,289,178	1,289,178	1,289,178
R-squared	0.396	0.542	0.709	0.265	0.637	0.770
VARIABLES	Panel B: Upper-Middle and Top					
	Upper-Middle			Top		
	Sales	Orders	Price	Sales	Orders	Price
Treat × Post	0.346***	0.364***	−0.0341***	0.199***	0.237***	−0.0476***
	(0.0273)	(0.0280)	(0.00857)	(0.0424)	(0.0372)	(0.0114)
Time FE	✓	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Observations	1,169,278	1,169,278	1,169,278	1,183,754	1,183,754	1,183,754
R-squared	0.273	0.688	0.818	0.513	0.767	0.856

Notes: Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 10: Heterogeneity in Multidimensional Performance

Panel A: Discoverability								
	Bottom		Lower-Middle		Upper-Middle		Top	
VARIABLES	Firm	Product	Firm	Product	Firm	Product	Firm	Product
Treat × Post	0.688***	0.691***	0.410***	0.414***	0.349***	0.355***	0.187***	0.192***
	(0.0314)	(0.0322)	(0.0258)	(0.0267)	(0.0236)	(0.0243)	(0.0301)	(0.0324)
Observations	1,332,364		1,289,178		1,169,278		1,183,754	
R-squared	0.628	0.624	0.699	0.695	0.729	0.727	0.780	0.775

Continued

Table 10 – Continued

Panel B: Expansion Effect

	Bottom		Lower-Middle		Upper-Middle		Top	
VARIABLES	%Sales	CVR	%Sales	CVR	%Sales	CVR	%Sales	CVR
Treat × Post	0.0486***	0.00504***	0.0351***	0.00539***	0.0247***	0.00392***	0.0217***	0.00339***
	(0.00455)	(0.000543)	(0.00389)	(0.00120)	(0.00284)	(0.000655)	(0.00392)	(0.000758)
Observations	1,332,364		1,289,178		1,169,278		1,183,754	
R-squared	0.516	0.468	0.603	0.547	0.646	0.504	0.700	0.602

Panel C: Quality

	Bottom		Lower-Middle		Upper-Middle		Top	
VARIABLES	Liability	Reviews	Liability	Reviews	Liability	Reviews	Liability	Reviews
Treat × Post	−0.00446***	−0.0482***	−0.00261***	−0.0343***	−0.00273***	−0.0342***	−0.000905	−0.0370***
	(0.000729)	(0.00473)	(0.000674)	(0.00370)	(0.000446)	(0.00563)	(0.000694)	(0.00473)
Observations	1,332,364		1,289,178		1,169,278		1,183,754	
R-squared	0.123	0.471	0.157	0.526	0.182	0.554	0.195	0.497

Panel D: Innovation

	Bottom		Lower-Middle		Upper-Middle		Top	
VARIABLES	Product	Category	Product	Category	Product	Category	Product	Category
Treat × Post	0.319***	0.203***	0.225***	0.147***	0.186***	0.116***	0.163***	0.0919***
	(0.0284)	(0.0126)	(0.0222)	(0.0134)	(0.0280)	(0.0163)	(0.0321)	(0.0179)
Observations	1,332,364		1,289,178		1,169,278		1,183,754	
R-squared	0.272	0.274	0.318	0.306	0.409	0.383	0.484	0.470

Notes: Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

6. Mechanism

In this section, we uncover the key mechanisms through which AI tools enhance firms' multidimensional performance and promote upward mobility for small firms. Our evidence suggests that two primary channels are at work: reductions in operating costs and the mitigation of information

asymmetries.

6.1 Cost Reduction

We employ two approaches to examine whether AI tools reduce firms' costs. First, in the e-commerce setting, customer service is a key component of firm operations. We use the logarithm of average human customer service time per order as a direct proxy for operating costs. Second, we exploit cross-regional variation in labor costs for identification. If AI reduces labor costs by substituting for human input, then sellers located in regions with higher labor costs should experience larger gains following AI adoption.

Table 11 reports changes in average human customer service time per order. The results show that AI adoption significantly reduces the time, and the effect is more pronounced for small and medium-sized firms. This pattern is consistent with a reduction in human input in customer service and provides direct evidence that AI lowers operating costs.

Furthermore, we examine heterogeneous effects across regions with different labor costs. Specifically, we measure regional labor costs using the average wages of employees in urban private wholesale and retail firms at the provincial level, as reported in the China Statistical Yearbook (2024). We then split the sample into high-cost and low-cost regions based on the median. Table 12 shows that firms in high labor-cost regions experience significantly larger increases in sales following AI adoption, and this effect is particularly strong for small firms. These findings are consistent with a cost-saving channel, suggesting that AI tools may substitute for human labor in customer service, content generation, and operational automation, thereby generating larger marginal gains in regions where labor is more expensive.

Overall, we provide evidence that AI tools reduce operating costs, with the effect being more pronounced for small firms. Relative to large firms, small firms are more constrained by labor input and operational efficiency, and therefore benefit more from the cost reductions induced by AI adoption. This heterogeneity further highlights cost savings as an important mechanism through which AI improves small firms' performance and facilitates their upward mobility.

6.2 Information Asymmetry Alleviation

We propose a second mechanism through which AI tools improve firm performance: the reduction of information asymmetry. We characterize information asymmetry along three dimensions, namely market price information, market demand information, and operational information.

First, for market price information, we define alignment between a firm's price adjustments and

Table 11: Average Customer Service Time Per Order

VARIABLES	(1)	(2)	(3)	(4)	(5)
	Average Customer Service Time Per Order				
	Total	Bottom	Lower-Middle	Upper-Middle	Top
Treat × Post	-0.117***	-0.144***	-0.126***	-0.0786***	-0.0561***
	(0.0109)	(0.0127)	(0.0144)	(0.0155)	(0.0179)
Time FE	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓
Observations	4,974,574	1,332,364	1,289,178	1,169,278	1,183,754
R-squared	0.707	0.605	0.731	0.775	0.797

Table 12: Regional Labor Costs

VARIABLES	(1)	(2)	(3)	(4)	(5)
	Sales				
	Total	Bottom	Lower-Middle	Upper-Middle	Top
Treat × Post × High Labor Cost	0.0429**	0.0743*	0.0581**	0.0274	0.0319
	(0.0215)	(0.0393)	(0.0237)	(0.0327)	(0.0313)
Treat × Post	0.506***	0.717***	0.402***	0.331***	0.179***
	(0.0232)	(0.0270)	(0.0258)	(0.0308)	(0.0376)
Time FE	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓
Observations	4,974,574	1,332,364	1,289,178	1,169,278	1,183,754
R-squared	0.662	0.396	0.265	0.273	0.514

Notes: Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

category-level median price changes as evidence of timely response to market signals. Column (1) of Table 13 shows that AI adoption significantly increases the likelihood of such alignment. Table 14 further shows that this effect is more pronounced among the smallest and the largest firms. For small firms, this is consistent with a reduction in information frictions and improved pricing decisions. For large firms, AI appears to play a complementary role by further improving the precision of pricing and sales decisions.

Second, for market demand information, we use the average product title length as a proxy for firms' ability to acquire and process market-relevant information. In e-commerce settings, product titles typically contain keywords designed to improve search visibility, and longer titles are generally associated with a better understanding of market trends and consumer search behavior. Column (2) of

Table 13 shows that AI adoption significantly increases product title length, with a more pronounced effect for small firms, as shown in Column (2) of Panel A in Table 14. This result suggests that AI improves firms' ability to acquire and utilize market demand information, thereby enhancing product discoverability.

Third, in terms of operational information, e-commerce firms frequently face information asymmetry arising from delays or frictions in communication during order fulfillment, particularly in logistics. Because pickup and delivery are typically handled by third-party logistics providers, firms that do not closely monitor shipment status may fail to detect delays or interruptions in a timely manner, which can adversely affect customer experience and firm reputation. We therefore use the 24-hour pickup ontime rate and the average delivery time as measures of operational information asymmetry. The results in Columns (3) and (4) of Table 13 show that AI tools significantly improve pickup timeliness and reduce logistics duration through automated reminders and information integration, providing direct evidence of reduced operational information frictions.

Finally, we construct a category-level measure of information asymmetry to examine whether AI has stronger effects in environments with greater informational frictions. Specifically, we use the average refund rate within each product category as a proxy for information asymmetry, where higher refund rates reflect more severe demand–supply mismatches. We then split categories into high and low information asymmetry groups based on the median refund rate in the baseline period. The results in Table 15 show that firms in high-information-asymmetry categories experience significantly larger gains from AI adoption, with particularly strong effects for small and medium-sized firms.

Overall, the evidence suggests that AI tools reduce information asymmetry by improving firms' ability to acquire and process both market and operational information. This channel is especially important for small firms, which face greater informational constraints.

7. Extension Discussion

7.1 Spillover Effect

A potential concern is that firms adopting AI may generate competitive spillovers that affect non-adopters, thereby biasing the estimated performance effects upward. To address this concern, we conduct the following analyses.

First, we test for the presence of market expansion effects. We treat each product category as a distinct market segment. Since all categories are exposed to AI tools, we implement a difference-in-differences design with a continuous treatment. Building on our earlier analysis, we posit that categories with greater information asymmetry are more strongly affected by AI. Accordingly, we

Table 13: Information Asymmetry

VARIABLES	(1) Firm Price Change	(2) Average Title Length	(3) 24h Pickup Ontime Rate	(4) Avg Delivery Time
Treat × Post	0.00905**	0.563***	0.0225***	−0.0230***
	(0.00298)	(0.0124)	(0.00151)	(0.00148)
Time FE	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Observations	4,974,574	4,974,574	4,974,574	4,974,574
R-squared	0.060	0.367	0.572	0.656

Notes: Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

use the baseline category-level return rate to measure the intensity of AI exposure and estimate the following specification:

$$y_{it} = \beta \times \text{Baseline Refund Rate}_i \times \text{Post}_t + \mu_i + \tau_t + \varepsilon_{it}$$

Baseline Refund Rate$_i$ is a continuous variable capturing a category's exposure to AI, measured by the baseline average refund rate. Post$_t$ equals 1 for periods after March 2024. μ_i and τ_t denote category and time fixed effects. The standard errors are all clustered in the category level. The results in Table 16 show that categories more strongly exposed to AI experience larger increases in sales, the number of new sellers and new product. These findings provide evidence of market expansion and suggest that AI adoption is not merely reallocating existing demand. This alleviates concerns regarding competitive spillovers. In addition, we find a decline in market concentration, which is consistent with the upward mobility of small firms.

Next, we examine potential competitive spillovers from the perspective of category-level AI adoption along two dimensions. First, we consider the role of AI adoption by large firms. If adopting firms exert substantial competitive spillovers on non-adopters, one would expect systematic differences in the estimated effects of AI across categories with relatively high versus low shares of large AI adopters. To test this, we compute, for each category, the share of large firms that have adopted AI during the sample period, where large firms are defined as those with annual sales exceeding RMB 5 million. As reported in Column (1) of Table 17, the interaction term is not statistically significant. Second, we examine overall category adoption rates. Specifically, we calculate the share of firms adopting AI within each category and assess whether this moderates the estimated treatment effects. We again find no evidence that categories with higher adoption rates

Table 14: Size Heterogeneity in Information Asymmetry

Panel A: Bottom

VARIABLES	(1) Seller Price Changes	(2) Average Title Length	(3) 24h Pickup Ontime Rate	(4) Avg Delivery Time
Treat × Post	0.0117*	0.675***	0.0285***	−0.0290***
	(0.00676)	(0.0148)	(0.00266)	(0.00238)
Observations	1,332,364	1,332,364	1,332,364	1,332,364
R-squared	0.059	0.335	0.499	0.562

Panel B: Lower-Middle

VARIABLES	(1) Seller Price Changes	(2) Average Title Length	(3) 24h Pickup Ontime Rate	(4) Avg Delivery Time
Treat × Post	0.00552	0.595***	0.0223***	−0.0208***
	(0.00557)	(0.0205)	(0.00278)	(0.00296)
Observations	1,289,178	1,289,178	1,289,178	1,289,178
R-squared	0.060	0.355	0.586	0.670

Panel C: Upper-Middle

VARIABLES	(1) Seller Price Changes	(2) Average Title Length	(3) 24h Pickup Ontime Rate	(4) Avg Delivery Time
Treat × Post	0.00125	0.499***	0.0140***	−0.0137***
	(0.00529)	(0.0217)	(0.00196)	(0.00319)
Observations	1,169,278	1,169,278	1,169,278	1,169,278
R-squared	0.060	0.376	0.617	0.708

Panel D: Top

VARIABLES	(1) Seller Price Changes	(2) Average Title Length	(3) 24h Pickup Ontime Rate	(4) Avg Delivery Time
Treat × Post	0.0136***	0.370***	0.0131***	−0.0192***
	(0.00430)	(0.0202)	(0.00248)	(0.00281)
Observations	1,183,754	1,183,754	1,183,754	1,183,754
R-squared	0.062	0.415	0.653	0.743

Notes: Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 15: Category Heterogeneity in Information Asymmetry

VARIABLES	(1)	(2)	(3)	(4)	(5)
			Sales		
	Total	Bottom	Lower-Middle	Upper-Middle	Top
Treat × Post × High Refund Rate	0.789***	2.046***	1.216*	0.487	0.0473
	(0.243)	(0.573)	(0.633)	(0.378)	(0.447)
Treat × Post	0.494***	0.668***	0.379***	0.324***	0.196***
	(0.0212)	(0.0314)	(0.0271)	(0.0263)	(0.0299)
Time FE	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓
Observations	4,974,574	1,332,364	1,289,178	1,169,278	1,183,754
R-squared	0.662	0.397	0.265	0.273	0.513

exhibit stronger performance gains (see Column (2) of Table 17).

Finally, we explore heterogeneity across categories with different levels of market competition. If competitive spillovers were an important channel, one would expect larger effects in more competitive markets. We measure market concentration using the average Herfindahl–Hirschman Index (HHI) at the category level during the sample period. Contrary to this prediction, we find that performance gains are more pronounced in more concentrated markets(see Column (3) of Table 17). This pattern not only weakens concerns about competitive spillovers but also aligns with an equalizing role of AI tools in the marketplace.

Taken together, these results provide little evidence that AI adoption generates economically meaningful competitive spillovers on non-adopting firms, suggesting that such spillovers are unlikely to be a primary driver of our main findings.

Table 16: Market Expansion

VARIABLES	(1) Sales	(2) New Seller	(3) New Product	(4) HHI
Baseline Refund Rate ×Post	0.0231***	0.00498***	0.00583***	−0.000142*
	(0.00612)	(0.00179)	0.00210	0.00008
Time FE	✓	✓	✓	✓
Category FE	✓	✓	✓	✓
Observations	423,900	423,900	423,900	423,900
R-squared	0.908	0.945	0.935	0.857

Table 17: Category Adoption Rate and Competition

VARIABLES	(1)	(2) Sales	(3)
Treat ×Post	0.557***	0.452*	0.518***
	(0.0345)	(0.230)	(0.0221)
Treat ×Post × Large Seller Adoption Rate	−6.147		
	(5.265)		
Treat ×Post × Adoption Rate		0.133	
		(0.395)	
Treat ×Post × HHI			1.849*
			(1.06)
Time FE	✓	✓	✓
Category FE	✓	✓	✓
Observations	4,974,574	4,974,574	4,974,574
R-squared	0.662	0.659	0.662

Notes: Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

7.2 Different Usage

Given substantial heterogeneity in both the intensity of AI adoption and the composition of module usage across firms, we further examine how these differences shape firm performance.

First, we classify firms into four groups based on their cumulative usage of two core AI features during the sample period, namely content generation and business analytics. Usage is measured within product categories and split at the median. The four groups are defined as follows: (1) LL firms, with low usage of both features; (2) HL firms, with high content generation usage and low business analytics usage; (3) LH firms, with low content generation usage and high business analytics usage; and (4) HH firms, with high usage of both features. The results in Table 18 show that, relative to the LL group, the other three groups exhibit stronger improvements across multiple performance dimensions, with the HH group displaying the largest gains. This pattern suggests that the value of AI tools reflects not just the intensity of individual module use, but also complementarities from joint adoption. Further decomposition shows that the content generation function primarily improves product presentation and content quality, thereby enhancing product performance, whereas the business analytics feature mainly operates through improved market insights and user understanding, contributing more fundamentally to customer acquisition and innovation.

Second, we examine the marginal effects of different AI modules. We categorize AI modules into five groups: content editing, content generation, data analytics, operations (including operations management, marketing, and product management modules), and services (including customer

service and logistics service modules). We then use standardized monthly usage frequency of each module at the firm level in our regressions. The results show that operational modules are most strongly associated with improvements in multidimensional firm performance, suggesting that AI plays a central role in process optimization and operational efficiency. In contrast, within content-related modules, editing has a stronger effect than generation. This likely reflects that firms are still in the learning stage with respect to more complex generative capabilities, whereas simpler editing tools are more readily adopted and more quickly translated into performance gains.

Overall, these findings highlight substantial structural heterogeneity in the effects of AI adoption. The performance impact of AI depends not only on usage intensity, but also on the complementarity of module combinations and firms' ability to effectively absorb and deploy different types of AI capabilities.

Table 18: Different Usage Frequencies

VARIABLES	(1) Sales	(2) %New Customer Sales	(3) Product Page Views	(4) Product Bad Rating Rate	(5) Seller Liability Rate in Disputes	(6) New Product Number
Treat × Post	0.301***	0.0264***	0.263***	-0.0227***	-0.00266***	0.147***
	(0.00352)	(0.00251)	(0.00376)	(0.00183)	(0.000473)	(0.00174)
Treat × Post × HL	0.341***	0.0134***	0.321***	-0.0393***	6.95e-06	0.0871***
	(0.00498)	(0.00339)	(0.00533)	(0.00259)	(0.000669)	(0.00246)
Treat × Post × LH	0.217***	0.0205***	0.251***	-0.00531*	-0.000690	0.133***
	(0.00501)	(0.00342)	(0.00535)	(0.00260)	(0.000672)	(0.00247)
Treat × Post × HH	0.635***	0.0329***	0.643***	-0.0411***	-0.00284***	0.275***
	(0.00497)	(0.00370)	(0.00532)	(0.00259)	(0.000668)	(0.00246)
Time FE	✓	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Observations	4,974,574	4,974,574	4,974,574	4,974,574	4,974,574	4,974,574
R-squared	0.665	0.598	0.750	0.505	0.140	0.358

8. Robustness Checks

8.1 Instrument Variable

Following the shift–share IV approach proposed by Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2022), we construct an individual-level shift–share instrument to address the endogeneity of

Table 19: Different Module Usage

VARIABLES	(1) Sales	(2) %New Customer Sales	(3) Product Page Views	(4) Product Bad Rating Rate	(5) Seller Liability Rate in Disputes	(6) New Product Number
Treat × Post × Edit	0.0269***	0.00126**	0.0273***	-0.000809***	-0.000213***	0.0682***
	(0.000731)	(0.000552)	(0.000864)	(0.000105)	(2.93e-05)	(0.00223)
Treat × Post × Generation	0.00787*	0.00391	0.00414	0.000245	(5.04e-05)	0.00650
	(0.00409)	(0.00309)	(0.00483)	(0.000588)	(0.000164)	(0.0125)
Treat × Post × Data	0.0287***	0.00169***	0.0360***	-0.00286***	-0.000144*	0.0124***
	(0.000980)	(0.000739)	(0.00116)	(0.000141)	(3.93e-05)	(0.00299)
Treat × Post × OMP	0.119***	0.00676***	0.108***	-0.00996***	-0.000556***	0.0524***
	(0.00171)	(0.00129)	(0.00202)	(0.000246)	(7.52e-05)	(0.00521)
Treat × Post × SL	0.0402***	0.00205***	0.0368***	0.000171	-0.000140***	0.00588***
	(0.00104)	(0.000784)	(0.00123)	(0.000149)	(4.16e-05)	(0.00317)
Time FE	✓	✓	✓	✓	✓	✓
Cohort FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Observations	4,974,574	4,974,574	4,974,574	4,974,574	4,974,574	4,974,574
R-squared	0.668	0.598	0.753	0.505	0.140	0.381

AI adoption. The instrument is defined as

$$IV = \underbrace{Firm\ Demand \times Province\ Digitalization}_{\text{share}} \times \underbrace{Peer\ Adoption\ Rate}_{\text{shift}}$$

where the shift component captures the adoption rate of other firms within the same product category, reflecting competitive pressure and information spillovers. The share component captures firms' exposure to AI shocks. It is measured as the interaction between each firm's historical demand for digital tools, proxied by the frequency of product modifications from January to September 2023, and province-level digitalization. The province-level digitalization index is constructed by normalizing and combining three measures: computers per 100 employees, websites per 100 firms, and the share of enterprises engaged in e-commerce.

This shift–share instrument exploits plausibly exogenous variation arising from differential exposure to peer adoption shocks across firms with heterogeneous pre-existing demand and regional digital infrastructure. First-stage regressions show that it strongly predicts AI adoption, and it passes both underidentification and weak identification tests, providing a valid source of causal variation.

In this section, we implement a panel fixed-effects instrumental variable regression, using the above variables as instruments for whether a firm adopts AI tools. The IV results in Table 20, 21 and 22 are consistent with the previous findings, confirming the robustness of our conclusions.

Table 20: IV: Firm Performance

VARIABLES	(1) Sales	(2) Orders	(3) Price
AI Adoption	0.362***	0.309***	0.0314
	(0.0363)	(0.0222)	(0.0205)
Time FE	✓	✓	✓
Firm FE	✓	✓	✓
Observations	4,974,574	4,974,574	4,974,574
R-squared	0.019	0.024	−0.000

Notes: Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 21: IV: Heterogeneous Effects

VARIABLES	(1)	(2)	(3)	(4)
	Sales			
	Bottom	Lower-Middle	Upper-Middle	Top
AI Adoption	0.556***	0.456***	0.469***	0.351***
	(0.0550)	(0.0327)	(0.0773)	(0.0598)
Time FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Observations	1,332,364	1,289,178	1,169,278	1,183,754
R-squared	0.031	0.024	0.021	0.016

Notes: Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 22: IV: Multidimensional Performance

VARIABLES	(1) Firm Page Views	(2) %New Customer Sales	(3) Product Negative Review Rate	(4) Avg Delivery Time	(5) Firm-Liability Dispute Rate	(6) New Product Number
AI Adoption	0.269***	0.0204***	−0.0677***	−0.0187***	−0.00209***	0.179***
	(0.0265)	(0.00506)	(0.00990)	(0.00542)	(0.000765)	(0.0285)
Time FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Observations	4,974,574	4,974,574	4,974,574	4,974,574	4,974,574	4,974,574

Notes: Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

8.2 Staggered DID

Because firms adopt the AI tool at different points in time, treatment follows a staggered adoption pattern. In this setting, the conventional two-way fixed effects estimator may assign negative weights when treatment effects are heterogeneous, potentially yielding biased estimates. To address this concern, we employ the imputation estimator developed by Borusyak et al. (2024) as a robustness check. This estimator is robust to staggered treatment timing and heterogeneous treatment effects and delivers consistent estimates under these conditions. The results in Table 23, 24 and 25 are qualitatively consistent with our baseline results.

Table 23: Staggered DID: Firm Performance

VARIABLES	(1) Sales	(2) Orders	(3) Price
Treat × Post	0.337***	0.317***	−0.000297
	(0.00343)	(0.00315)	(0.00159)
Time FE	✓	✓	✓
Firm FE	✓	✓	✓
Observations	4,974,574	4,974,574	4,974,574

Notes: Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 24: Staggered DID: Heterogeneous Effects

VARIABLES	(1)	(2)	(3)	(4)
	Sales			
	Bottom	Lower-Middle	Upper-Middle	Top
Treat × Post	0.524***	0.369***	0.340***	0.220***
	(0.00680)	(0.00643)	(0.00673)	(0.00820)
Time FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Observations	1,332,364	1,289,178	1,169,278	1,183,754

Notes: Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

8.3 Synthetic DID

Finally, following Arkhangelsky et al. (2021), we implement the synthetic difference-in-differences estimator as an additional robustness check. Because firms exhibit substantial heterogeneity in category, size, and adoption timing, we partition the sample along these three dimensions and

Table 25: Staggered DID: Multidimensional Performance

VARIABLES	(1) Seller Page Views	(2) %New Customer Sales	(3) Product Negative Review Rate	(4) Avg Delivery Time	(5) Firm-Liability Dispute Rate	(6) New Product Number
AI Adoption	0.319***	0.0131***	−0.0134***	−0.0194***	−0.00145***	0.0657***
	(0.00350)	(0.000545)	(0.000401)	(0.000493)	(0.000125)	(0.00149)
Time FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Observations	4,974,574	4,974,574	4,974,574	4,974,574	4,974,574	4,974,574

Notes: Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

estimate the synthetic DID model separately within each industry–size–cohort cell. Firm size is defined using the quartile classification introduced above and indexed from 1 (smallest) to 4 (largest). Cohorts are determined by the month of first AI tool adoption, spanning July 2024 to June 2025 and indexed from 1 to 12.

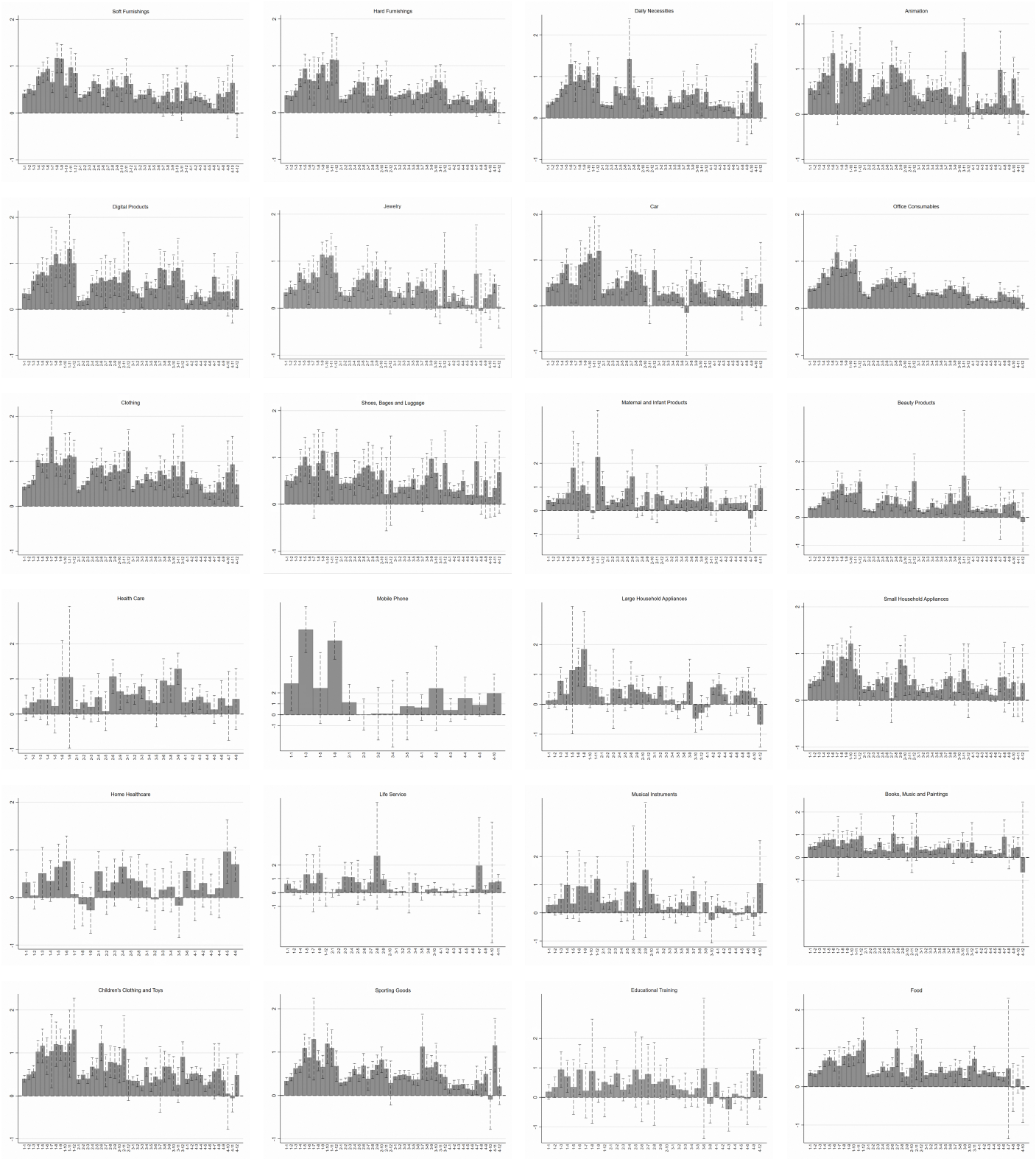
Figure 4 presents the results. Each panel corresponds to a specific category, and the vertical axis reports the estimated coefficients for each size–cohort cell in sequence. For instance, "1–1" denotes firms in the bottom size quartile that first adopted the AI tool in July 2024, while "1–2" denotes firms in the same quartile that first adopted in August 2024, and so forth. In some categories, certain size–cohort cells contain too few observations to construct a valid donor pool for the synthetic control procedure, making estimation infeasible; these cells are therefore omitted. Overall, the synthetic DID estimates align with the baseline results.

9. Conclusion

The rapid adoption of artificial intelligence in business operations has raised fundamental questions about how emerging technologies affect firm performance and competitive dynamics. Rather than assuming uniform benefits or costs, the impact of AI should be understood through its influence on firms' productivity, resource allocation, and strategic positioning within digital markets. Digital platforms offer a particularly informative context for studying these effects because they both mediate technology diffusion and shape firms' interactions with customers, competitors, and markets. Examining AI adoption in this setting reveals how technology-driven changes propagate across heterogeneous firms and under what conditions AI fosters growth, innovation, and broader market participation.

Using large-scale firm-level panel data from a major Chinese e-commerce platform, this study

Figure 4: Synthetic DID by Category, Size and Cohort



evaluates the performance implications of a platform-enabled AI system that integrates generative content tools with analytics features. Employing a PSM-DID design alongside multiple complementary identification strategies, we find that AI adoption substantially improves commercial outcomes. Firms that integrate the tool experience significant revenue growth, primarily driven by increased transaction volumes, while also achieving measurable gains in discoverability, operational and product quality, and innovation. These patterns indicate that AI deployment reshapes operational capacity rather than merely generating short-term demand fluctuations.

Importantly, the benefits are unevenly distributed, with smaller firms gaining disproportionately. Enterprises with lower baseline sales realize much larger relative gains, and their improvements extend beyond revenue into broader aspects of organizational capability. Evidence on the underlying mechanisms indicates that AI relaxes key constraints by lowering operating costs and alleviating market information asymmetries. The stronger effects observed among smaller firms imply that when AI is provided through an integrated, low-friction platform environment, it can reduce pre-existing capability gaps rather than exacerbate them. The results also speak to the broader market consequences of AI diffusion. We find evidence of market expansion rather than pure business stealing.

These findings carry several practical implications. For platform designers, the results highlight that accessibility, integration depth, and ease of use are central determinants of AI's competitive impact. Tools that are embedded into routine workflows and require minimal complementary investment can encourage wider participation and sustain marketplace dynamism. For smaller enterprises, AI adoption should be seen as an organizational upgrading strategy that fosters learning, experimentation, and capability accumulation rather than simply as an automation decision. From a policy perspective, interventions that lower adoption barriers and standardize access to AI can support more balanced digital development and market growth.

Several limitations deserve consideration. The empirical setting, while rich and internally robust, reflects the institutional characteristics of a single platform ecosystem; effects may differ in markets with alternative governance structures or higher adoption frictions. Moreover, the analysis does not capture potential long-term equilibrium adjustments, competitive crowding effects, or price dynamics as AI diffusion intensifies. Finally, although we document operational upgrading, we do not directly observe internal task reallocation or consumer welfare implications. Future research linking AI deployment to organizational restructuring and broader welfare outcomes would further illuminate its structural consequences. Overall, our findings suggest that AI's transformative impact depends on how it is integrated into firms' operations and market environments. When AI is deployed in a low-cost and tightly integrated manner, AI can expand access to capabilities, generate new growth

opportunities, and strengthen competitive vitality rather than entrench existing advantages.

References

Alekseeva, L., Azar, J., Giné, M., Samila, S., and Taska, B. (2021). The demand for ai skills in the labor market. *Labour economics*, 71:102002.

Arendt, L. (2008). Barriers to ict adoption in smes: how to bridge the digital divide? *Journal of systems and information technology*, 10(2):93–108.

Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G. W., and Wager, S. (2021). Synthetic difference-in-differences. *American economic review*, 111(12):4088–4118.

Ayyagari, M., Beck, T., and Demirguc-Kunt, A. (2007). Small and medium enterprises across the globe. *Small business economics*, 29(4):415–434.

Babina, T., Fedyk, A., He, A., and Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics*, 151:103745.

Bäck, A., Hajikhani, A., Jäger, A., Schubert, T., and Suominen, A. (2022). Return of the solow-paradox in ai? ai-adoption and firm productivity. Technical report, Lund University, CIRCLE-Centre for Innovation Research.

Bajgar, M., Criscuolo, C., and Timmis, J. (2021). Intangibles and industry concentration: Supersize me.

Bar-Gill, S., Brynjolfsson, E., and Hak, N. (2024). Helping small businesses become more data-driven: A field experiment on ebay. *Management Science*, 70(11):7345–7372.

Beck, T., Demirguc-Kunt, A., and Levine, R. (2005). Smes, growth, and poverty: Cross-country evidence. *Journal of economic growth*, 10(3):199–229.

Bloom, N., Genakos, C., Sadun, R., and Van Reenen, J. (2012). Management practices across firms and countries. *Academy of management perspectives*, 26(1):12–33.

Borusyak, K., Hull, P., and Jaravel, X. (2022). Quasi-experimental shift-share research designs. *The Review of economic studies*, 89(1):181–213.

Borusyak, K., Jaravel, X., and Spiess, J. (2024). Revisiting event-study designs: robust and efficient estimation. *Review of Economic Studies*, 91(6):3253–3285.

Bresnahan, T. F., Brynjolfsson, E., and Hitt, L. M. (2002). Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. *The quarterly journal of economics*, 117(1):339–376.

Brynjolfsson, E. and Hitt, L. M. (2003). Computing productivity: Firm-level evidence. *Review of economics and statistics*, 85(4):793–808.

Brynjolfsson, E., Rock, D., and Syverson, C. (2021). The productivity j-curve: How intangibles complement general purpose technologies. *American Economic Journal: Macroeconomics*, 13(1):333–372.

Cai, J. J., Gu, X., Sheng, L., Xia, M., Zhao, L., and Zhu, W. (2025). Ai as" co-founder": Genai for entrepreneurship. *arXiv preprint arXiv:2512.06506*.

Calvino, F. and Fontanelli, L. (2023). A portrait of ai adopters across countries: Firm characteristics, assets' complementarities and productivity. *OECD Science, Technology and Industry Working Papers*, 2023(02).

Cengiz, D., Dube, A., Lindner, A., and Zipperer, B. (2018). The effect of minimum wages on low-wage jobs: evidence from the united states using a bunching estimator. Technical report, London School of Economics and Political Science, LSE Library.

Czarnitzki, D., Fernández, G. P., and Rammer, C. (2023). Artificial intelligence and firm-level productivity. *Journal of Economic Behavior & Organization*, 211:188–205.

da Silva Marioni, L., Rincon-Aznar, A., and Venturini, F. (2024). Productivity performance, distance to frontier and ai innovation: Firm-level evidence from europe. *Journal of Economic Behavior & Organization*, 228:106762.

Damioli, G., Van Roy, V., and Vertesy, D. (2021). The impact of artificial intelligence on labor productivity. *Eurasian Business Review*, 11(1):1–25.

Dell'Acqua, F., McFowland III, E., Mollick, E. R., Lifshitz-Assaf, H., Kellogg, K., Rajendran, S., Krayer, L., Candelon, F., and Lakhani, K. R. (2023). Navigating the jagged technological frontier: Field experimental evidence of the effects of ai on knowledge worker productivity and quality. *Harvard business school technology & operations mgt. Unit working paper*, (24-013).

Eisfeldt, A. L., Schubert, G., and Zhang, M. B. (2023). Generative ai and firm values. Technical report, National Bureau of Economic Research.

Goldberg, S. and Lam, H. T. (2025). Generative ai in equilibrium: Evidence from a creative goods marketplace.

Goldfarb, A. and Tucker, C. (2019). Digital economics. *Journal of economic literature*, 57(1):3–43.

Goldsmith-Pinkham, P., Sorkin, I., and Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, 110(8):2586–2624.

Hagiu, A. and Wright, J. (2025). Artificial intelligence and competition policy. *International Journal of Industrial Organization*, page 103134.

Igna, I. and Venturini, F. (2023). The determinants of ai innovation across european firms. *Research Policy*, 52(2):104661.

Kim, D. et al. (2020). Internet and smes' internationalization: The role of platform and website. *Journal of International Management*, 26(1):100690.

McElheran, K., Yang, M.-J., Brynjolfsson, E., and Kroff, Z. (2025). The rise of industrial ai in america: Microfoundations of the productivity j-curve (s). *Available at SSRN 5036270*.

Otis, N., Clarke, R., Delecourt, S., Holtz, D., and Koning, R. (2024). The uneven impact of generative ai on entrepreneurial performance.

Petersen, M. A. and Rajan, R. G. (2002). Does distance still matter? the information revolution in small business lending. *The journal of Finance*, 57(6):2533–2570.

Tadelis, S. (2016). Reputation and feedback systems in online platform markets. *Annual review of economics*, 8(1):321–340.

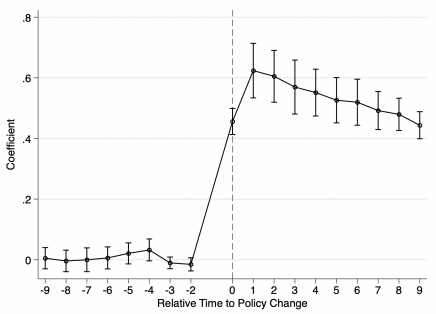
Tambe, P., Hitt, L., Rock, D., and Brynjolfsson, E. (2020). Digital capital and superstar firms. Working Paper

28285, National Bureau of Economic Research.

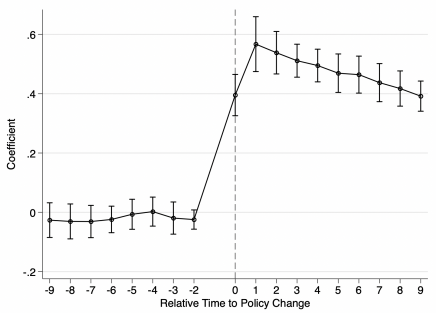
Zeng, S., Wang, X., and Sun, T. (2025). Artificial intelligence, domain ai readiness, and firm productivity. *arXiv preprint arXiv:2508.09634*.

A. Appendix

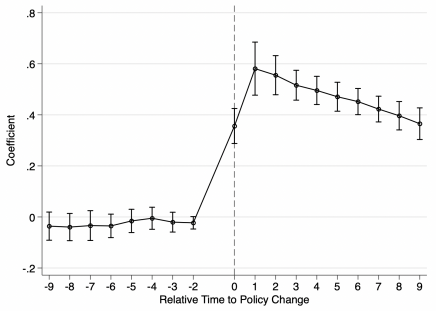
Figure 5: Parallel Trend Tests



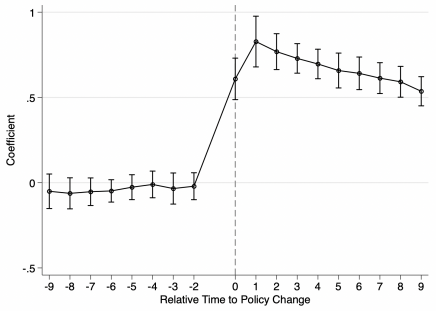
(a) Sales



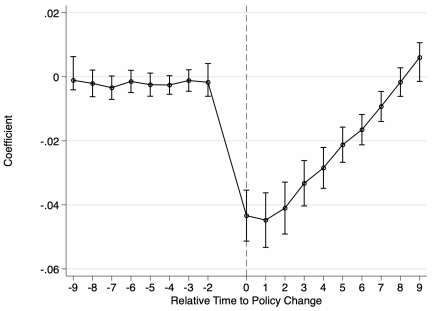
(b) Orders



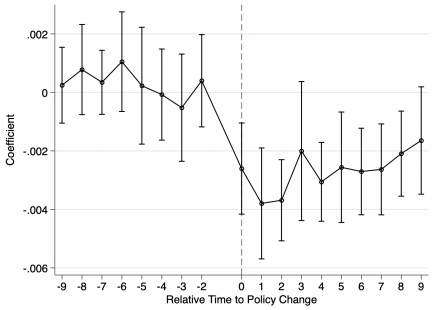
(c) Firm Page Views



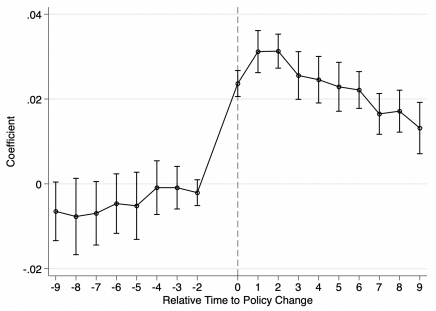
(d) %New Customer Sales



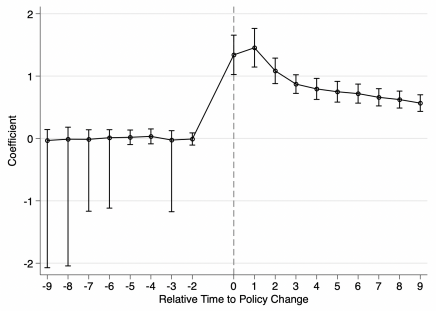
(e) Bad Reviews



(f) Firm Liability



(g) Pickup



(h) New Product Sales

Table 26: Long-term Effect: Sales

	(1)	(2)	(3)	(4)	(5)
VARIABLES			Sales		
Treat ×Post_s	0.539***	0.753***	0.438***	0.377***	0.250***
	(0.0227)	(0.0238)	(0.0227)	(0.0241)	(0.0350)
Treat ×Post_m	0.491***	0.753***	0.393***	0.254***	0.143***
	(0.0220)	(0.0287)	(0.0263)	(0.0263)	(0.0347)
Treat ×Post_l	0.397***	0.656***	0.316***	0.137***	-0.000334
	(0.0164)	(0.0313)	(0.0307)	(0.0274)	(0.0267)
Observations	6,020,256	1,505,086	1,505,042	1,505,042	1,505,086
R-squared	0.662	0.396	0.265	0.275	0.514

Notes: $Post_s$ indicates the period 1–3 months following AI adoption, $Post_m$ indicates 4–6 months post-adoption, and $Post_l$ indicates the period beyond 6 months after adoption. Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 27: Long-term Effect: Multidimensional Performance

VARIABLES	Panel A: Bottom and Lower-Middle							
	Bottom				Lower-Middle			
	View	Review	Dispute	Innovation	View	Review	Dispute	Innovation
Treat ×Post_s	0.683***	−0.0496***	−0.00442***	0.336***	0.421***	−0.0362***	−0.00252***	0.242***
	(0.0224)	(0.00436)	(0.000725)	(0.0205)	(0.0236)	(0.00458)	(0.000711)	(0.0196)
Treat ×Post_m	0.692***	−0.0326***	−0.00428***	0.216***	0.354***	−0.0194***	−0.00284***	0.136***
	(0.0311)	(0.00354)	(0.000976)	(0.0228)	(0.0291)	(0.00298)	(0.000851)	(0.0180)
Treat ×Post_l	0.556***	−0.00913***	−0.00308**	0.185***	0.248***	0.00362	−0.00190*	0.117***
	(0.0331)	(0.00325)	(0.00117)	(0.0193)	(0.0313)	(0.00320)	(0.00105)	(0.0174)
Observations	1,332,364	1,332,364	1,332,364	1,332,364	1,289,178	1,289,178	1,289,178	1,289,178
R-squared	0.624	0.472	0.123	0.274	0.695	0.527	0.157	0.319
VARIABLES	Panel B: Upper-Middle and Top							
	Upper-Middle				Top			
	View	Review	Dispute	Innovation	View	Review	Dispute	Innovation
Treat ×Post_s	0.377***	−0.0383***	−0.00305***	0.211***	0.232***	−0.0463***	−0.00118*	0.203***
	(0.0233)	(0.00441)	(0.000529)	(0.0218)	(0.0310)	(0.00597)	(0.000623)	(0.0316)
Treat ×Post_m	0.289***	−0.0219***	−0.00173***	0.103***	0.156***	−0.0275***	−0.000472	0.107***
	(0.0258)	(0.00381)	(0.000517)	(0.0186)	(0.0295)	(0.00394)	(0.000796)	(0.0237)
Treat ×Post_l	0.188***	−0.00217	−0.000493	0.0826***	0.0211	0.000751	−0.000161	0.0333**
	(0.0335)	(0.00210)	(0.000608)	(0.0188)	(0.0284)	(0.00248)	(0.00133)	(0.0160)
Observations	1,169,278	1,169,278	1,169,278	1,169,278	1,183,754	1,183,754	1,183,754	1,183,754
R-squared	0.727	0.617	0.182	0.410	0.776	0.653	0.180	0.485

Notes: $Post_s$ indicates the period 1–3 months following AI adoption, $Post_m$ indicates 4–6 months post-adoption, and $Post_l$ indicates the period beyond 6 months after adoption. Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.