The Effect of Platform-developed AI Price Recommendations Adoption on E-Commerce Platform Sales Distribution

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Short Paper

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Abstract

Past studies on the long-tail phenomenon in digital markets or platforms have examined how buyer-side technologies affect the sales distribution of products. However, these studies did not fully explain how emerging platform-developed AI pricing agents, as a seller-side technology, can affect the sales distribution of products on e-commerce platforms. To fill this gap, we use a proprietary dataset from an e-commerce platform in Asia to empirically quantify the effect of sellers' adoption of platform-developed AI price recommendations on the aggregate sales distribution of products. By employing a Heckman-type model for product-level analysis, we find that AI pricing adoption leads to a more diverse sales distribution of products, and this effect is accentuated when market competition is more intense. Our category-level analysis affirms this finding. Mechanism evaluations reveal products' prices recommended by AI pricing agents help improve sellers' product visibility, conversation rate, and average quantity purchased.

Keywords: AI pricing, Sales distribution, Market competition, E-commerce platform

Introduction

Platform-developed AI pricing agents have proliferated in recent years, including those for sharing economy platforms (e.g., Airbnb's smart pricing (Zhang et al. 2021), Zillow's Zestimate (Fu et al. 2022), Uber's surge pricing (Guda and Subramanian 2019)) and e-commerce platforms (e.g., eBay). By providing AI price recommendations, these AI pricing agents attempt to assist sellers set prices more optimally in response to demand dynamics and to boost sales revenue. Whereas prior research (Chen et al. 2016) has shown how sellers' adoption of platform-developed AI price recommendations affects product-level outcomes (e.g., products' sales revenue), there are limited studies examining how this adoption impacts market-level outcomes, such as the aggregate sales distribution of products (i.e., sales concentration or diversity[1] that reveals how sales revenue at the market level is concentrated or spread across products).

[1] It is necessary to distinguish several constructs. Sales diversity in our study refers to sales revenue diversity and describes the distribution of market share across various products. Sales concentration pertains to the degree to which sales revenue is monopolized by popular or top-selling products. While these two constructs are interrelated, they are not identical. Consider two scenarios: in scenario 1, sales revenue for products A, B, and C are $10, $2, and $2 respectively. In scenario 2, sales revenue for products A, B, and C are $2, $10, and $2. Here, compared with scenario 1, scenario 2 shows decreased sales concentration as the top product (A) has less revenue, but sales diversity remains the same, demonstrating the distinctiveness of these constructs. Besides, these two constructs are at the market level in our paper and different from individual-level sales diversity (Lee and Hosanagar 2019). Additionally, they are

Notably, the unique attributes of AI pricing differentiate it from traditional pricing techniques, enhancing its impact on market-level outcomes like sales distribution. First, AI pricing enables the automated generation of price recommendations without requiring human input, thereby reducing the dependency on humans' decisions and cognitive ability to predict demand responses to their pricing decisions (Chen et al. 2016). Second, its capability to harness big data and computational power allows for pricing that takes into account each product's unique attributes and dynamic market conditions. These unique features suggest that AI pricing could have a more significant and nuanced effect on sales distribution.

The empirical analysis of sales concentration or diversity on e-commerce platforms is practically important because a more diverse sales distribution is generally preferred by their stakeholders. For platforms, a more diverse sales distribution can provide a certain degree of market competition and encourage sellers' lower prices to maintain platform competitiveness (Brynjolfsson et al. 2003). For buyers, higher sales diversity increases the likelihood of finding products that meet buyers' needs and preferences (Lee and Hosanagar 2019). For sellers, a less skewed sales distribution can reduce sellers' dependence on a few highly popular products and therefore, decrease the vulnerability to demand shocks. As such, it is vital to systematically evaluate how the adoption of AI price recommendations by sellers affects products' sales distribution on e-commerce platforms. Specifically, if sellers' adoption of AI price recommendations increases sales diversity, it is beneficial to promote such an AI pricing technology since there can be positive social welfare implications for the individual stakeholders and the market or platform.

In terms of academic significance, we pin-point two related research gaps to motivate our paper. First, albeit past research has studied sales distribution in digital markets about digital artifacts or technologies such as internet channels (Brynjolfsson et al. 2011), mobile apps and channels (Park et al. 2020), and recommendation systems (Lee et al. 2020; Lee and Hosanagar 2019), this strand of research has only analyzed buyer-side technologies. These buyer-side technologies are designed to improve the demand-side usage of a marketplace by facilitating product or service discovery, comparison, and purchase for buyers. In contrast, seller-side technologies target the supply-side usage of a marketplace to improve the efficiency and effectiveness of sellers' operations. The nature of usage difference makes it inadequate to apply the past research on buyer-side technologies to directly explain the supply-side causes of changes in sales distribution due to seller-side technologies. Importantly, the emerging platform-developed AI pricing agent is a seller-side technology that directly guides sellers' pricing decisions. This seller-side usage nature of AI pricing agents makes it less clear how their adoption by sellers can influence consumers' purchases and, in turn, impact the sales distribution of products. Moreover, existing AI pricing studies have proposed inconsistent conjectures on the net impact of the adoption of AI price recommendations on the sales distribution of products (Fu et al. 2022; Zhang et al. 2021) which also motivates the objective of our research. To fill this gap and to reconcile the conflicting assertions by way of new empirical evidence, we propose our first research question (RQ 1): *How do sellers' adoption of AI price recommendations for products affect the aggregate sales distribution of products on an e-commerce platform?*

Second, to further understand how sellers' adoption of AI price recommendations can affect aggregate sales distribution, exploring the moderating role of market competition intensity on the relationship between such adoption and sales distribution is important. Market competition intensity is generally considered to be the degree to which a product faces competition in its market (Jaworski and Kohli 1993). Assuming that a product's low sales revenue is due to a seller's inability to set competitive prices to respond to market competition conditions and that AI recommended pricing can equalize this pricing differential across sellers, then the potential effect of adopting AI price recommendations in improving the sales diversity of products is anticipated to be more pronounced in markets with higher competition intensity. However, to our best knowledge, this has not been studied in past AI pricing and competition studies which have mainly examined how adoptions of AI pricing lead to different market competition intensity outcomes (Asker et al. 2022; Assad et al. 2022; Calvano et al. 2020). To fill this gap, we propose our second research question (RQ 2): *How does market competition intensity moderate the relationship between sellers' adoption of AI price recommendations and aggregate sales distribution of products on an e-commerce platform?*

To answer our research questions, we collected a proprietary dataset from a prominent e-commerce platform in Asia that introduced AI price recommendations for products sold by sellers in the platform's

different when compared to product diversity or product variety which refers to the variety of different product types available in the market.

monthly promotional campaigns. Specifically, we chose the sellers and their products that were involved in three campaigns from July 2021 (i.e., pre-"treatment" or before the launch of AI pricing) to August and September 2021 (i.e., post-"treatment"). To address the self-selection of AI pricing adoption by sellers and to quantify the adoption impact on sales distribution, we use a Heckman-type model at the seller-product level to derive causal inferences on the sales revenue diversity. We also conduct a product category level analysis via examining the Gini coefficient for the sales revenue of products in each category of a campaign.

We uncover several key findings. First, we find that sellers' adoption of AI price recommendations can lead to a more diverse sales distribution of products by boosting the sales revenue of originally less popular products at the product level and reducing the Gini coefficient at the category level. In terms of the marginal effects, at the product level, we find that products with a 0.1 unit increase in relative sales rank (i.e., popularity decreases) receive 20.4% higher sales revenue from adopting AI recommended prices. At the category level, a 0.1 unit increase in sellers' AI pricing adoption share of products in a category can reduce the Gini coefficient of the category sales revenue by 0.0022 unit. Second, the positive effect of AI pricing adoption on the diversity of sales distribution is more pronounced when market competition is more intense. We argue that this is because AI pricing can better incorporate market competition information and thus assist sellers in setting competitive (i.e., lower) prices to better compete against other sellers. Third, our evaluation of mechanisms related to consumer behaviors shows that after sellers' adoption of AI price recommendations, less popular products garner higher visibility to consumers, sales conversion rate, and average quantity purchased per consumer, resulting in higher sales diversity.

Our research provides several contributions. First, we are among the first to empirically investigate how and why seller-side technologies, specifically sellers' adoption of platform-developed AI pricing agents, affect aggregate sales distribution of products. We thus complement prior research on the effect of buyer-side technologies on sales distributions in digital markets (Brynjolfsson et al. 2011; Lee et al. 2020). Second, we extend AI pricing impact studies (Chen et al. 2016; Zhang et al. 2021) and AI pricing and competition studies (Assad et al. 2022; Calvano et al. 2020) by empirically documenting how sellers' adoption of AI pricing increases the diversity of aggregate sales distribution of products, and how market competition intensity positively moderates this effect. Third, we add to past studies on long-tail sales distribution by evaluating the underlying mechanisms related to products' visibility, conversion rate, and average quantity purchased. Fourth, we offer practical insights for platform owners to address sales distribution inequity and sub-optimal market participation problems on e-commerce platforms through the adoption of AI pricing.

Literature Review and Theoretical Background

Long-tail Sales Distribution in Digital Markets

Aggregate sales distributions of products sold in digital markets have been extensively studied in the past literature on the long-tail phenomenon in e-commerce. Past related studies have only focused on the effects of buyer-side technologies, ranging from internet channels (Brynjolfsson et al. 2011), mobile apps and channels (Park et al. 2020), and AI-related technologies such as recommendation systems (Lee et al. 2020; Lee and Hosanagar 2019). On the resultant sales diversity effect, prior studies of buyer-side technologies have asserted supply-side causes such as the lower cost of offering a wide product assortment (Brynjolfsson et al. 2006) and demand-side causes such as allowing consumers to be exposed to more of the less popular products in the consumer decision process (Lee et al. 2020). Moreover, studies of personalized recommendation systems suggest that not only do these less popular products receive higher visibility, but they also better match consumer preferences when recommended by personalized recommenders, resulting in a higher sales conversion rate (Li et al. 2022). However, this research stream has not analyzed how seller-side technologies, such as AI pricing agents or recommendations, can affect the sales distribution of products. Notably, compared with buyer-side technologies which directly impact consumers' purchase behaviors, it is unclear whether and how sellers' adoption of AI pricing can influence the sales diversity of products by optimizing pricing decisions. This gap in the literature leads us to study the relation between sellers' adoption of AI pricing and the aggregate sales distribution of products on an e-commerce platform.

AI Pricing and Sales Performance

Prior studies have examined the impact of AI pricing adoption on seller-level sales outcomes (e.g., revenue enhancement) (Chen et al. 2016; Cheung et al. 2017) and sellers' adoption behaviors (Caro and de Tejada

Cuenca 2023). As for market-level outcomes, past studies have primarily focused on market competition conditions (e.g., shifts in market margins) (Asker et al. 2022; Assad et al. 2022; Calvano et al. 2020), while largely neglecting the domain of sales distribution. Specifically, results from Zhang et al. (2021) imply indirectly that the adoption of AI pricing can lead to a more diverse sales distribution, through showing that African American hosts can improve sales revenue more from the adoption of AI price recommendations compared to white American hosts, thus mitigating the revenue gap between these two types of hosts on Airbnb. However, the reduced revenue gap between African American and white American hosts does not necessarily mean higher sales diversity for all host types on the platform. Moreover, Fu et al. (2020) has qualitatively argued that the adoption of AI pricing agents may exacerbate sales distribution inequity. For example, AI pricing agents' predicted demand curve and price recommendations may skew towards popular products, and therefore, sellers' adoption of AI price recommendations for less popular products may not boost sales revenue. Thus, a comprehensive evaluation of how sellers' adoption of AI pricing affects aggregate sales distribution of products is necessary.

AI Pricing and Market Competition Intensity

Recent research on AI pricing and market competition has primarily focused on how the adoption of AI pricing can lead to different market competition outcomes (Asker et al. 2022; Assad et al. 2022; Calvano et al. 2020). However, prior studies have not analyzed how market competition intensity moderates the relationship between sellers' adoption of AI price recommendations and the aggregate sales distribution of products. Past marketing studies have found that consumers are likely to purchase the product with a lower price, relative to that of rival products or its competitors (Bolton et al. 2003). This leads us to anticipate that sellers or products facing stronger market competition necessitate more advanced pricing capabilities to effectively respond to competitors' prices. Previous studies on AI pricing and market competition (Assad et al. 2022) have proven that AI pricing can effectively take competitors' prices into account to make the pricing decision. Thus, if sellers' adoption of AI pricing agents can provide an equitable pricing capability to set more competitive prices to improve sales, then it is expected that the potential impact of adopting AI price recommendations on sales diversity can be strengthened in markets with more intense competition. However, prior literature has not analyzed how market competition intensity moderates the relationship between sellers' adoption of AI price recommendations and the aggregate sales distribution of products, thereby motivating further investigation to elucidate this relation. We thus aim to offer actionable insights for both sellers and platform owners, enabling them to make more strategic choices of adopting AI pricing.

Empirical Analysis and Results

Research Context and Data

Our dataset is collected from one of the largest e-commerce platforms in Asia, which introduced AI price recommendations in August 2021 for the monthly promotional campaigns for specific products[2]. These AI price recommendations were generated through a machine learning algorithm that employed a combination of three models, similar to Ye et al. (2018). The first model was designed to predict future product demand (i.e., prospective sales volume). The second model was to estimate consumers' price elasticity of demand (i.e., the relationship between price and sales volume). These two models included multiple factors such as seller rating, product rating, and competitors' prices, and were trained exclusively using data from past monthly promotional campaigns. The third model integrated the first two to determine the optimal AI price recommendations for each product to meet the pre-defined platform revenue target. During our sample period, AI price recommendations were provided to sellers exclusively in monthly promotional campaigns, but not during the regular sales periods. Sellers participating in the campaigns were required to select products and set each product's prices within a predefined period before the campaign's launch. Price modifications were allowed within this period but disallowed post this period. The AI price recommendation was prominently displayed for sellers to follow when sellers decide a product's price in the price-setting box for each campaign (see Figure 1). And sellers were advised to set each product's price equal to or lower than the AI recommended price for each product. We select products participating

[2] The platform-developed AI price recommendations nearly cover all products except the following special cases: 1) new products with new attributes which have not been included in the design of the AI pricing algorithm, 2) products with predicted sales (from AI pricing agent) to be zero no matter how prices change.

in all three campaigns from July 2021 (i.e., pre-AI pricing launch) to September 2021. Our final dataset included 219,906 observations for a seller-product-campaign level panel sample, covering 73,302 products in 2,348 product categories from 9,998 sellers in three campaigns.

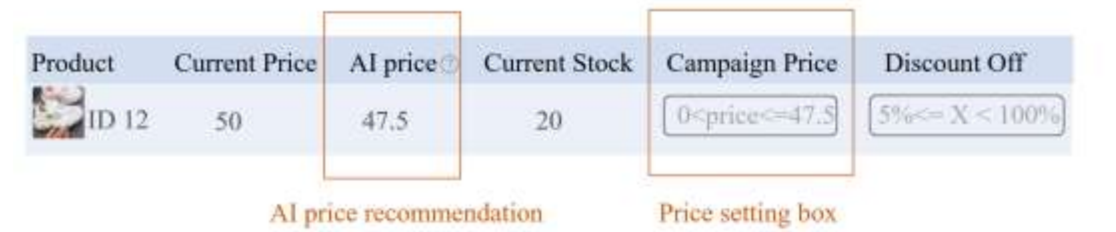

Figure 1. Settings for using AI price recommendations on sellers' page

Variables

Our study aims to investigate the effect of sellers' AI pricing adoption on the sales distribution of products at both the product level and the product category level. At the product level, our dependent variable is sales revenue ($Revenue_{ijt}$), measuring the seller i's gross merchandise value for a product j in the campaign t. Our main independent variable is AI price recommendation adoption ($Adopt_{ijt}$), a binary variable indicating whether seller i adopts the AI price recommendation for product j in campaign t. $Adopt_{ijt}$ equals to 1 if the product's campaign price is equal to or lower than the AI recommended price[3].

Our moderating variables include market competition intensity ($Competition_{ij}$), which is proxied by the total number of products excluding product j in the category that seller i is listing product j ($NumPro_{ij}$). Generally, more rival products indicate more intense market competition.

We also include a set of control variables (*Controls*) in our empirical model as follows. First, we include the distance between AI price recommendations and seller-set prices since lower AI recommended prices can influence sellers' adoption intention and sales performance after adoption (Schultze et al. 2015). Second, we include product review rating and volume to control for product quality and product popularity. Third, we include a binary variable indicating whether products employ other promotion tools (e.g., free shipping). Fourth, we include a seller's rating and average message response time to control for the seller's service quality. Fifth, we include a seller's number of followers and a binary variable indicating whether the seller is a flagship store seller to control for seller popularity and store type. Sixth, we include a seller's average page views of the platform's AI pricing feature information to control for the sellers' AI knowledge. Seventh, we include sellers' single-multi-homing attribute for the focal and rival platforms. Eighth, we include the median prices of product categories for each campaign to control buyers' price sensitivity across campaigns.

At the category level, we use Gini coefficient ($Gini_{kt}$) as our dependent variable to measure the sales distribution of products. A lower Gini coefficient indicates a more diverse sales distribution of products (Brynjolfsson et al. 2011). Our independent variable, moderating variable, and control variables are identical to the prior-mentioned variables at the product level but aggregated at the category level. Specifically, our independent variable is measured by the proportion of products adopting AI price recommendations in category k ($Adopt_{kt}$). The moderating variable is proxied by the total number of products in category k ($Competition_k$). We use the average values of control variables as category-level controls and include the total sales revenue of category k in each campaign to control for the market size. We finally use the median prices of all products in each campaign to control for buyers' price sensitivity.

Econometric Models

In our setting, the differences in sales distribution before and after the launch of AI pricing come from those who adopt the AI recommended prices. In this sense, our estimates are more representative of a local

[3] Referring to Figure 1, the price-setting box suggests a seller set a price equal to or lower than the AI recommended price before the seller fill in the product's price. There is also a pop-up message to emphasize this suggestion when sellers move their mouse pointer to the question mark beside the "AI price" header.

average treatment effect (LATE). To account for the potential self-selection of AI pricing adoption, we conduct a product-level analysis by employing a Heckman-type model (Kumar et al. 2018) as follows:

$$Adopt_{ijt}^{*} = \partial_0 + \partial_1 Controls + \zeta_k + \Psi_t + e_{ijt} \tag{1}$$

$$\begin{aligned} Ln(Revenue_{ijt}) = \ell_0 + \ell_1 Adopt_{ijt} + \ell_2 Adopt_{ijt} * Popularity_{ij} + \ell_3 Adopt_{ijt} * Competition_{ij} \\ + \ell_4 Adopt_{ijt} * Competition_{ij} * Popularity_{ij} + \ell_5 Controls + \ell_6 IMR_{ijt} + \theta_{ij} + \Psi_t + \varepsilon_{ijt} \end{aligned} \tag{2}$$

where ζ_k is a category fixed effect, θ_{ij} is a seller-product fixed effect[4], and Ψ_t is a campaign fixed effect. Equation (1) is a probit model to capture the sellers' self-selected adoption decision where $Adopt_{ijt}^{*}$ is a latent variable of seller *i*'s utility for AI pricing adoption for product *j*. We include all prior-mentioned control variables. Equation (2) is our main model where $Adopt_{ijt}$ is a binary variable indicating if a seller adopted the AI price recommendation for a focal product. The indicator $Adopt_{ijt} = 1$ if $Adopt_{ijt}^{*} \geq 0$ and is zero otherwise. $Popularity_{ij}$ refers to the relative sales rank[5] of product *j*, i.e., computed via dividing the ordinal sales rank of product *j* in a specific category before the launch of AI pricing by the total number of products in the product category. Following Brynjolfsson et al. (2011), we include the interaction term between $Adopt_{ijt}$ and $Popularity_{ij}$ to examine the heterogeneous effect of adoption across products with different pre-treatment popularity, so as to infer the effect of AI pricing adoption on sales diversity of products at the seller-product level. The coefficient of the three-way interaction term between $Adopt_{ijt}$, $Popularity_{ij}$, and $Competition_{ij}$ then shows how this heterogeneous effect may vary with market competition intensity, and thus indicates how market competition intensity moderates the effect of AI pricing adoption on sales diversity of products. $Revenue_{ijt}$ was incremented by 1 (to accommodate for zero-sales products) during the semi-log model estimation following Cole and Sokolyk (2018). e_{ijt} and ε_{ijt} are correlated via a bivariate normal distribution. Following Saboo et al. (2016), we compute the predicted inverse Mills ratio (IMR) based on equation (1) and include this ratio in equation (2) to take the selection process into account.

Our category-level model is specified as an ordinary least squares (OLS) model with two-way fixed effects:

$$Gini_{kt} = \beta_0 + \beta_1 Adopt_{kt} + \beta_2 Adopt_{kt} * Competition_k + \beta_3 Controls_{kt} + \zeta_k + \Psi_t + \eta_{kt} \tag{3}$$

where $Gini_{kt}$ is the Gini coefficient of sales revenue for products in category *k* of campaign *t*, $Adopt_{kt}$ is the AI pricing adoption share, and $Competition_k$ is the market competition intensity. We include all category-level controls previously mentioned. η_{kt} denotes the residual error term. Notably, β_1 and β_2 are the focal estimated coefficients to answer our first and second research questions respectively.

Results

The model estimation results of equation (2) and equation (3) are presented in Table 1. In column (1), the positive coefficient of the interaction term (ℓ_2=1.857, p-value<0.001) shows that products with a 0.1 unit increase in relative sales rank (i.e., popularity decreases) receive 20.4%[6] higher sales revenue from adopting AI recommended prices, thus implying that less popular products get a sales revenue boost after adopting AI pricing, i.e., sales distribution of products becomes more diverse. Besides, the positive coefficient of the three-way interaction term in column (2) (ℓ_4=0.513, p-value<0.001) shows that the revenue-boosting effect of AI pricing for products with lower popularity is strengthened when market competition intensity is higher. These results suggest that sellers' adoption of AI price recommendations has a stronger impact on the aggregate sales distribution when the market competition intensity is higher. Moreover, these results imply that AI pricing can enhance sales diversity by identifying competitive prices (i.e., lower prices) in

[4] In our data, each product is unique to each seller. Thus, the seller-product fixed effect captures products' within-seller time-invariant heterogeneity.

[5] For products with zero sales revenue, we keep their relative sales rank identical. For example, if there are four products A, B, C, and D in a category where only A has positive sales revenue, the ordinal sales rank of A is 1, and that of B, C and D are 2. The relative sales rank of A is 0.25, and that of B, C, and D are 0.5.

[6] The marginal effect is calculated as: Exp(1.857*0.1)-1=0.204

response to market price competition. In column (3), the negative coefficient of *Adopt* (β_1 =-0.022, p-value<0.05) indicates that a 0.1 unit increase in sellers' AI pricing adoption share of products in a category can reduce the Gini coefficient of the category sales revenue by 0.0022 unit, which provides more direct evidence that AI pricing adoption can enhance the sales diversity of products in the market. Besides, the negative coefficient of the interaction term in column (4) (β_2 =-0.021, p-value<0.001) shows AI pricing adoption can lead to an additional 0.021 unit decrease in the Gini coefficient when the logarithm of the total number of products in a category, i.e., the indicator of market competition intensity, increases by 1 unit.

	(1)	(2)	(3)	(4)
	Product-level Analysis		Category-level Analysis	
	Main Effect	Moderating Effect	Main Effect	Moderating Effect
Variables	DV = Ln(*Revenue*)		DV = *Gini*	
Adopt	0.305*** (0.080)	0.762*** (0.086)	**-0.022**** (0.010)	0.010 (0.011)
*Adopt*Popularity*	**1.857***** (0.045)	0.172** (0.089)		
*Adopt*Competition*		-0.118*** (0.007)		**-0.021***** (0.004)
*Adopt*Competition*Popularity*		**0.513***** (0.021)		
IMR	-0.476*** (0.050)	-0.521*** (0.050)		
Control Variables	YES	YES	YES	YES
Seller-product fixed effects	YES	YES	YES	YES
Campaign fixed effects	YES	YES	YES	YES
Observations	219,906	219,906	7,044	7,044
R-square	0.679	0.681	0.887	0.887
Notes. *** p<0.01, ** p<0.05, * p<0.1. Values in parentheses are robust standard errors. Variables in columns (1)-(2) are product-level measures, and those in columns (3)-(4) are category-level measures.				

Table 1. Model Estimation Results at Product and Category Levels

Mechanism Analysis

We explore how sellers' adoption of AI price recommendations of products can be related to consumers' purchasing behaviors and elucidate how this relationship contributes to changes in the sales distribution of products. Following past studies (Lee et al. 2020; Li et al. 2022), we use three alternative dependent variables for equation (2), including total page view of products (PV_{ijt}), conversion rate of products (CVR_{ijt}), and average quantity bought by a consumer (AOQ_{ijt})[7]. The model estimation results are presented in Table 2. In column (1), we find that products' AI pricing adoption can boost the visibility of less popular products more. Specifically, a 0.1 unit increase in a product's relative sales rank (i.e., lower popularity) is associated with a 10.4% additional boost in the product's page views after adopting AI pricing. In general, less popular products have lower visibility due to their uncompetitive prices, since during product search processes, consumers typically filter products by price in ascending order or based on specific price ranges[8], making lower-priced products more noticeable. Thus, by adopting AI recommended prices that are more competitive (i.e., lower prices), less popular products can become more visible to consumers. In column (2), we find less popular products exhibit an increase in conversion rate after AI pricing adoption, compared to more popular products. Specifically, a 0.1 unit increase in a product's relative sales rank leads to a 0.0027 unit rise in the product's conversion rate after adopting AI recommended prices. This is perhaps because the lower popularity of specific products can be due to uncompetitive prices that inhibit consumers'

[7] Conversion rate is calculated by dividing product *j*'s sales volume by its total page views. Average quantity bought is calculated by dividing product *j*'s total sales volume by total buyer volume. Both variables are coded as missing if the denominator in the division operation is zero.

[8] The search results webpage of the e-commerce platform we studied offers a search filter option where products can be ordered by ascending/descending prices and a specific price range can be entered.

purchases. Thus, less popular products can achieve a higher conversion rate after adopting AI pricing, since reference price theory (Bolton et al. 2003) implies that consumers are more likely to purchase products with lower prices (relative to rival ones) which enhance their perceived utility. Results in column (3) reveal that products with a 0.1 unit increase in relative sales rank (i.e., lower popularity) bring about a 2.87% higher average quantity purchased per consumer by adopting AI pricing. This implies that AI pricing agent's competitive prices can motivate consumers to buy more units of less popular products.

	(1)	(2)	(3)
Dependent Variables	*Ln(PV$_{ijt}$)*	*CVR$_{ijt}$*	*Ln(AOQ)$_{ijt}$*
Adopt	0.404*** (0.111)	-0.003 (0.006)	-0.011 (0.052)
*Adopt*Popularity*	**0.988***** (0.052)	**0.027***** (0.004)	**0.283***** (0.023)
IMR	-0.341*** (0.069)	-0.003 (0.004)	-0.028*** (0.032)
Control Variables	YES	YES	YES
Seller-product fixed effects	YES	YES	YES
Campaign fixed effects	YES	YES	YES
Observations	219,906	165,870	59,471
R-square	0.726	0.468	0.637
Notes. *** p<0.01, ** p<0.05, * p<0.1. The values in parameters are robust standard errors.			

Table 2. Model Estimation Results for Mechanism Analysis

Conclusions and Future Work

This paper makes the following contributions by exploring how and to what extent sellers' adoption of platform-developed AI price recommendations of products affects the aggregate sales distribution of products on an e-commerce platform. First, this paper is among the pioneers to investigate how and why seller-side technologies affect aggregate sales distribution of products. By conducting empirical analyses at the product and category levels, we find that sellers' adoption of AI pricing can increase the sales diversity of products on an e-commerce platform. This complements past research on long-tail sales distribution in digital markets and AI pricing studies. Second, we contribute to the AI pricing impact and competition literature by uncovering that the effect of AI pricing adoption on increasing sales diversity is more pronounced when market competition intensity is higher. Third, we add to past studies on long-tail sales distribution by evaluating the underlying mechanisms where sellers' adoption of AI pricing can result in higher products' visibility, conversion rate, and average quantity purchased per consumer for less popular products. As this is an ongoing research, we acknowledge a few limitations that can be addressed in future work. First, the potential endogeneity of sellers' self-selected adoption is not fully addressed in the current category-level analysis, which needs other identification strategies such as the instrumental variables method. Second, we plan to analyze the impact of adoption on sales distribution at the seller level to provide more insights. Third, we plan to uncover the underlying mechanisms that drive the effects of AI pricing adoption on the sales distribution of products. For instance, we plan to analyze the heterogenous effects on utilitarian and hedonic products' sales distribution, as the former may face stronger price competition.

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