A Spatial Analysis of Artificial Intelligence and Market Competition

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Extended Abstract

This study aims to establish a spatial oligopoly model to analyze how AI technologies influence market structure, competitive behavior and social welfare. With the rapid advancement of digital transformation, Artificial Intelligence (AI) has become a key driver of economic transitions, introducing structural changes to business operations, market structures, and competitive behaviors. AI technologies, encompassing algorithmic pricing, personalized services, data analytics, and machine learning, significantly enhance large-scale data processing and decision-making efficiency. However, the widespread adoption of AI has also raised concerns about digital disparities, particularly the technological gap between large and small firms. This issue has drawn increasing attention from digital and competition regulators worldwide due to its implications for market competition and potential risks of inequality and monopolization.

This study proposes a modified spatial oligopoly model to analyze how AI technologies influence market competition with a specific focus on the digital divide between large and small firms. While large firms benefit from AI investments through cost reductions and quality improvements, small firms face significant challenges due to resource constraints, further exacerbating technological disparities. Despite significant advancements in areas such as algorithmic pricing, tacit collusion, data privacy, and machine learning predictions, economic research on the interplay between market competition and technological disparities remains relatively limited. This study seeks to bridge this gap by examining the relationship between AI, market competition, and digital disparities, analyzing their effects on market structure and competitive equilibria. By integrating AI into a spatial oligopoly framework, this work explores how AI reshapes competition, pricing strategies, firm entry behavior, and social welfare. Furthermore, it investigates AI's role in addressing issues of excessive or insufficient market entry. Combining theoretical modeling with empirical insights, the research aims to propose policy recommendations for digital and competition strategies to promote fair competition, enhance consumer welfare, and improve social welfare outcomes.

While recent research has extensively explored algorithmic pricing (Calvano et al., 2020a, 2020b, 2021), privacy and data protection (Choi et al., 2019, and Rhodes and Zhou, 2024), and machine learning applications for prediction (Mullainathan and Spiess, 2017), comparatively less attention has been directed toward

technological gaps and AI's impact on market competition. This research plan attempts to ask the following two questions: How do AI-related barriers to entry and market concentration affect competition and innovation? How does the concentration of AI development among a few firms contribute to economic and competitive inequalities?

These two main research questions address some part of essential issues in understanding the economic and competitive impacts of AI. First, AI's high resource demands, including data, algorithms, and computational power, create significant barriers to entry for AI implementation. This may foster market concentration, where dominant firms with superior AI capabilities solidify their positions, making it difficult for smaller or new entrants to compete. Second, the technological divide arising from the concentration of AI development among a few firms or nations exacerbates inequalities. Firms with advanced AI capabilities can leverage these technologies to gain a competitive edge, leaving others behind. This divide influences firm-level competition and contributes to broader economic disparities between regions and countries. Recent policies like the EU's Digital Markets Act are essential to address these challenges and foster fair competition. This research contributes to understanding AI's broader economic impacts, particularly in underexamined areas like competition and technological inequality.

Various studies on AI and digital economics are on the rise. Among them, AI-powered pricing algorithms allow firms to optimize prices but risk enabling tacit collusion. Studies such as Calvano et al. (2020a, 2020b, 2021) show how algorithms can unintentionally align prices, reducing competition and harming consumers. Regulatory measures are needed to address these challenges. AI-driven personalized pricing has intensified privacy concerns. Studies by Rhodes & Zhou (2024) and Choi et al. (2019) highlight the ethical challenges of using consumer data. Frameworks like the GDPR aim to balance innovation and privacy, ensuring responsible AI deployment. While machine learning applications, such as predictive modeling (Mullainathan & Spiess, 2017), provide valuable insights, they fall outside this study's scope.

We apply a modified spatial oligopoly model to explore how AI-driven investments and competition impact market structures, focusing on pricing, quality, and firm entry in AI environments. The model builds upon foundational spatial frameworks such as the Salop circular model, integrating unique elements to address the competitive interplay between a dominant, AI-capable central firm and smaller, traditional firms positioned along a circular market. Our analysis examines three core aspects:

1. AI Investment Effects: We model how AI investment by the central firm enhances product quality and reduces costs, influencing its competitive position relative to smaller firms. This includes examining the trade-offs between quality improvement and cost reduction, as well as their implications for market pricing and firm profitability.
2. Equilibrium Market Structure: By incorporating free entry for smaller firms, we analyze how AI adoption affects the number of entrants in the market. This includes conditions under which markets experience

excess or insufficient entry, depending on the relative strength of AI-driven advantages.

3. Consumer and Social Welfare: The model evaluates consumer surplus and social welfare outcomes, balancing the benefits of AI-enabled efficiencies against potential market distortions, such as concentration or exclusion of smaller firms.

Our study also relates closely to the literature on excess entry, particularly in examining how market structures are shaped by entry decisions under varying conditions. Mankiw and Whinston (1986) established that free entry often leads to excessive firm numbers due to the business-stealing effect, where entrants fail to account for the external costs imposed on incumbents. Our approach extends this framework by incorporating AI-driven cost reductions and quality improvements, which amplify both the entry incentives and the associated inefficiencies. In this line of literature, for instance, Amir et al. (2014) generalize the excess entry theorem by showing that business-stealing effects dominate under convex cost structures, while business-enhancing effects can lead to under-entry. Our research explores the market entry influenced by technological disparities, aligning with findings from Woo (2013), who emphasized the role of consumption status effects in exacerbating excessive entry. Unlike prior studies, we consider the impact of AI on entry barriers and market structure. In addition, Bhaskar and To (2004) highlighted that even with perfect price discrimination, free entry results in inefficiencies due to the marginal firm's contribution being relative to an inefficient benchmark. Our research parallels this by examining AI's role in shifting competitive baselines, thereby altering welfare outcomes. While the literature often assumes homogeneous firms, our approach accounts for technological heterogeneity, aligning with findings by Vives and Vravosinos (2022) on overlapping ownership's impact on entry.

Polo (2016) and Ino and Matsumura (2022) explored entry outcomes in homogeneous and differentiated product markets, showing that AI-driven cost reductions might bring entry levels closer to social optima under capacity constraints. Recent studies like Rhodes and Zhou (2024) highlight how AI-enabled personalized pricing intensifies competition but exacerbates inequalities when only a few firms have access to advanced technologies. Bisceglia et al. (2024) demonstrated how AI-driven cost reductions in low-barrier markets could lead to adverse selection, allowing high-cost firms to enter inefficiently. Their work suggests raising entry costs to ensure that only efficient firms participate. Toshimitsu (2023) investigated network goods markets, finding that excess entry is prevalent in firm-specific networks but insufficient in industry-wide systems with elastic network effects. Empirical contributions have also shaped this discussion. Clay et al. (2002) and Pozzi (2013) studied the effects of entry on pricing and market expansion, finding that entry benefits consumers through competition but leads to inefficiencies if unregulated. Duch-Brown et al. (2017) examined the consumer electronics sector, revealing how online-offline integration affects entry and market structure. These findings underscore the role of AI in reshaping competition through algorithmic pricing and real-time data analytics.

This research integrates these insights into a spatial oligopoly model to analyze how AI-driven innovations impact market entry, firm behavior, and social welfare. By incorporating AI-enabled cost reductions, quality improvements, and algorithmic pricing, it evaluates the trade-offs between competitive intensity and market efficiency. This aligns with contemporary studies like Bisceglia et al. (2024) and Toshimitsu (2023), offering theoretical advancements and practical policy recommendations for regulating AI-driven markets.

This research aligns closely with issues faced by competition authorities, particularly regarding AI's impact on market structures and anticompetitive practices. Marar (2024) emphasizes the risks of AI facilitating collusion and monopolization, underscoring the need for antitrust policies to prevent AI-driven barriers that entrench monopolistic practices or exclude competitors. Similarly, FTC (2022) identifies implicit collusion and algorithmic decision-making as challenges for competition enforcement, as these practices can reinforce market dominance and harm consumer choice. This research contributes by examining AI's role in amplifying market concentration and entry barriers, offering insights into how competition authorities can adapt regulations to address AI-specific challenges, promote fair competition, and balance innovation with consumer protection.

Model Setting

To model AI and market competition, we consider a modified circular model following the approaches outlined in Salop (1978), Balasubramanian (1998), Hakenes and Schnabel (2010), Madden and Pezzino (2011), Guo and Lai (2014), and Tseng and Guo (2022). In this model, there is a large firm, indexed by firm 0, with the option to invest in AI, situated at the center of the circle. Surrounding this central firm are N equidistant, relatively smaller firms, denoted by firms 1, 2… N, located along the circumference of the circle at 0, 1/N, 2/N… (N-1)/N. This setup allows us to explore the competition and interaction between a technologically advanced central firm and peripheral firms with more traditional operational models. For example, in the competitive environment of retail channels or bookstores, a dominant online retailer or bookstore (such as Amazon) has sufficient data and funds to invest in AI. However, traditional small retailers (small bookstores) lack the resources to invest in AI.

Consumers are evenly spaced along the circumference of a circle with a length of one, maintaining a uniform density of one. Each consumer invariably purchases exactly one unit of the product. The utility function for consumers x, U_i, when purchasing from firm i by paying p_i (where i=0, 1, 2, .. N), can be expressed as follows:

$$U_1 = v - p_1 - t\,x\,,$$

$$U_i = v - p_i - t\left|x - \frac{i-1}{N}\right|, \quad i = 2..N,$$

$$U_0 = v + k_q\,e - p_0 - \lambda\,.$$

The variable v represents the reservation value of the product for the consumer, indicating the highest price a consumer is willing to pay and ensuring full market coverage. The set $\{p_i\}$ includes the prices that these firms charge for their products. The parameter t denotes the cost per unit of distance for transactions with smaller firms, which includes any transportation or distance-related expenses. The term λ is a specific cost associated only with purchases from the central firm. The variable e measures the level of AI investment by the central firm. The product $k_q\, e$ represents the quality enhancement resulting from this investment, which increases the perceived value of the product to consumers. Meanwhile, $k_c\, e$ reflects cost reductions in the unit cost of production, attributable to efficiencies gained from implementing AI technology. It is assumed that λ is small enough $(\lambda \leq \frac{t}{2N})$ to ensure that all firms are not rendered redundant in the market.

The marginal consumer who is indifferent between buying from firm 0 and firm 1 is determined by $\hat{x}_1 = \frac{p_0 - p_1 + \lambda - k_q\, e}{t}$. Then, the profits of firms can be expressed as follows:

$$\pi_1 = 2(p_1 - c)\, \hat{x}_1 - F, \tag{1}$$

$$\pi_0 = (p_0 - (c - k_q\, e))N(\tfrac{1}{N} - 2\hat{x}_1) - e^2/2\,. \tag{2}$$

Equation (1) calculates firm 1's profit by multiplying the margin (price minus cost) by its demand. Equation (2) derives the profit for the central firm, with the price set by firm 0 reduced by the net cost savings from AI $(c - k_q\, e)$, the market share as the portion of the market not covered by small firms, and the quadratic cost associated with the AI investment $e^2/2$.

Consider the following game structure: In the first stage, small firms have the opportunity to enter the market, each incurring a fixed cost F. In the second stage, the central firm selects its AI investments. Following this, all firms engage in price competition in the third stage. Finally, consumers make their purchasing decisions based on the prices and available products. This sequence allows for the analysis of strategic interactions between entry decisions, AI investments, and competitive pricing.

Consumer surplus (*CS*) can be determined by integrating the utility functions for the different market segments. Specifically, consumer surplus is calculated as $CS = 2N \int_0^{\hat{x}_1} U_1 \mathrm{d}x + 2N \int_{\hat{x}_1}^{\frac{1}{2N}} U_0 \mathrm{d}x$. This equation represents the total utility consumers gain from purchasing products. The first integral calculates the consumer surplus for those buying from small firms, up to the point where they are indifferent, while the second integral captures the surplus for consumers buying from the central firm. The social welfare (SW) is then calculated by adding consumer surplus to the total profits of the firms in the market: $SW = CS + N\pi_1 + \pi_0$.

Equilibrium Analysis on AI and Market Competition

By differentiating the profit functions with respect to prices and considering the symmetry of the market structure, we derive the following equilibrium first-order conditions and corresponding equilibrium prices:

$$p_i(e) = c + \frac{\lambda - e(k_q + k_c)}{3} + \frac{t}{6N},\ \mathrm{i} = 1,2,..\mathrm{N}, \tag{3}$$

$$p_0(e) = c - \frac{\lambda + e(2k_c - k_q)}{3} + \frac{t}{3N}. \tag{4}$$

Substituting the prices into the profit function for firm 0, and differentiating with respect to AI investment, we obtain the following optimal AI investment:

$$e^* = \frac{4(k_c + k_q)(t - \lambda N)}{9t - 4N(k_c + k_q)^2}. \tag{5}$$

This equation determines the optimal level of AI investment for the central firm by considering the trade-offs between competition among large and small firms, cost savings, and quality enhancements provided by AI. The degree of the cost-reducing parameter and the quality-improving parameter are assumed to be moderate enough to ensure an interior solution. Notably, the second-order condition is satisfied, confirming the stability and optimality of the solution.

In the entry stage, the equilibrium number of small firms is determined by the zero profit condition, leading to:

$$N^* = \frac{4\lambda + 9F - t\sqrt{9F(9F + 8\lambda) - 32F\left(k_c + k_q\right)^2}}{4\left(\lambda^2 + 2F(k_c + k_q)^2\right)}. \tag{6}$$

This equation ensures that when the market reaches equilibrium, the small firms are making zero profits, balancing the cost factors λ and F, and the combined effects of the cost-reducing and quality-improving parameters k_c and k_q.

With the above derivation, the impact of AI on equilibrium and market structure is demonstrated as the following first proposition.

Proposition 1. (a) With a fixed number of small firms, AI lowers small firms' prices. The central firm's price may increase if quality improvements outweigh cost reductions significantly or decrease otherwise. (b) Optimal AI investment rises with its ability to improve quality and cut costs but declines as the number of small firms increases due to reduced benefits from competition. (c) Free market entry leads to more small firms as AI becomes more effective at enhancing quality and reducing costs. (d) The number of small firms increases with the central firm's specific cost disadvantage when AI effects are minor but decreases as AI's benefits become substantial, enabling the central firm to offset cost disadvantages.

Proposition 1 illustrates several ways that AI investment impacts market pricing and competition. Proposition 1(a) addresses how AI investment influences the pricing strategies of both small and central firms. When small firms are given a fixed number, AI investments typically lead to a reduction in their prices. This outcome can be attributed to the efficiencies AI technology brings, such as reduced operating costs and enhanced production processes for the central firm, which lead small firms to offer their products at lower prices by competition. Conversely, the impact of AI on the central firm's pricing depends on the relative strengths of cost reduction versus quality enhancement brought about by AI. If the quality improvement component is more than twice the cost reduction, the central firm may increase prices, leveraging improved product quality to target higher-paying segments.

Proposition 1(b) elaborates on how the optimal level of AI investment is influenced by its capabilities to enhance quality and reduce costs. As the AI technology's ability to improve quality and reduce costs increases, so does the incentive for firms to invest more in AI. This is because greater benefits from AI directly translate to competitive advantages in the market. However, the presence of more small firms dilutes these advantages as the market becomes more competitive, reducing the marginal gains from AI investment, thereby making AI investments less attractive.

Proposition 1(c) explores the entry and exit of small firms in response to AI effectiveness. As AI technology becomes more capable of reducing costs and improving product quality, it creates a more favorable market environment, encouraging more small firms to enter. This phenomenon can be understood as the market becoming more accessible to new entrants who can now more effectively compete against established players due to lower initial cost barriers and enhanced product offerings made possible by AI. Finally, Proposition 1(d) considers how the specific cost (λ) associated with the central firm interacts with the impact of AI on market structure. Initially, as λ increases, indicating higher costs exclusive to the central firm, more small firms find it viable to enter the market due to reduced competitive pressure from the central firm. However, as the effectiveness of AI escalates, enabling significant cost reductions and quality improvements, the central firm can counterbalance the high λ cost, making it more competitive and potentially discouraging the entry of new small firms. Thus, the relationship between the number of small firms and λ becomes contingent on the strength of the AI benefits, illustrating a complex interplay between technology, market entry costs, and competition among firms.

Next, we can discuss the issue of excess entry. To simplify the notation, we assume *t=1* and $k_c = k_q = k$, which allows us to express the social welfare function as follows:

$$SW(N) = \frac{(1-\lambda N)(9(2-5\lambda N)+16Nk^2(1+2\lambda N))}{N(9-16Nk^2)^2} + v - c - NF - \frac{1}{4N}. \tag{7}$$

This equation shows how social welfare is affected by the number of firms, N, in the market. It evaluates the welfare increase from market entry, factoring in how costs, competition, and firm numbers influence product pricing and quality. The term $v-c$ represents basic consumer surplus, NF totals the fixed costs for all firms, and $\frac{1}{4N}$ indicates the potential negative effects on social welfare from distance costs. Then, we have the following result for the association between AI and market structure.

Proposition 2: When the effects of AI are significant, and the competitive advantage of the central firm is relatively weak, the market tends to experience excess entry of small firms. Conversely, when the effects of AI are minimal, the market tends to experience insufficient entry.

Proposition 2 explains that when the effects of AI are substantial, but the competitive advantage of the central firm is relatively weak, the equilibrium number of firms in the market tends to be higher than optimal, indicating excess entry. Conversely, when the impact of AI is minimal, the number of firms tends to be lower than optimal, indicating insufficient entry.

In addressing the issue of excess entry and its modulation by AI, this result parallels and extends several notable studies within the previous literature. According to Mankiw and Whinston (1986), excess entry can lead to socially suboptimal outcomes due to the business-stealing effect, where the aggregate market profits and overall welfare decrease as too many firms crowd the market. The role of AI in this context can be compared to Amir, Erickson, and Jin (2017), who explore the foundations of differentiated product markets and the implications for market structure. Further, the introduction of AI into market entry analysis aligns with recent explorations of technological impacts on competitive strategies, such as those discussed by Athey, Bryan, and Gans (2020), who examine the allocation of decision-making authority between humans and AI. These authors highlight how AI can transform decision-making processes, potentially leading to new forms of market behavior that could exacerbate or mitigate traditional concerns such as excess entry.

Moreover, the impact of AI on market entry has been scrutinized under the lens of algorithmic competition and the potential for new types of market equilibria, as detailed by Asker, Fershtman, and Pakes (2022). They investigate how AI and algorithmic tools reshape pricing strategies and competitive behaviors, offering a modern perspective on how technology influences market structures and the potential for excess or insufficient entry.

To illustrate the above association between AI and optimal market structure. In Figure 1, the parameters considered in the graph (with v=5, k =c=1, F=1/50), and varying λ from 0.1 to 0.3 and k from 0.05 to 0.2, lead to a scenario where the number of small firms ranges from 2 to 4. The equilibrium prices range approximately from 1 to 1.2, with the price at the central firm being higher than that at the small firms. This graph and the corresponding analysis provide insights into how AI impacts market structure, potentially leading to either overcrowding or underrepresentation of firms depending on the strength of AI and the competitive conditions. Such analysis is crucial for understanding market environment in industries where AI and other technological advancements play significant roles. The graph illustrates the relationship between the cost-reducing and quality-improving parameter k and the specific cost λ associated with purchasing from the central firm. It identifies regions of excess and insufficient entry of small firms into the market under different conditions of AI effectiveness and competition between the central and small firms.

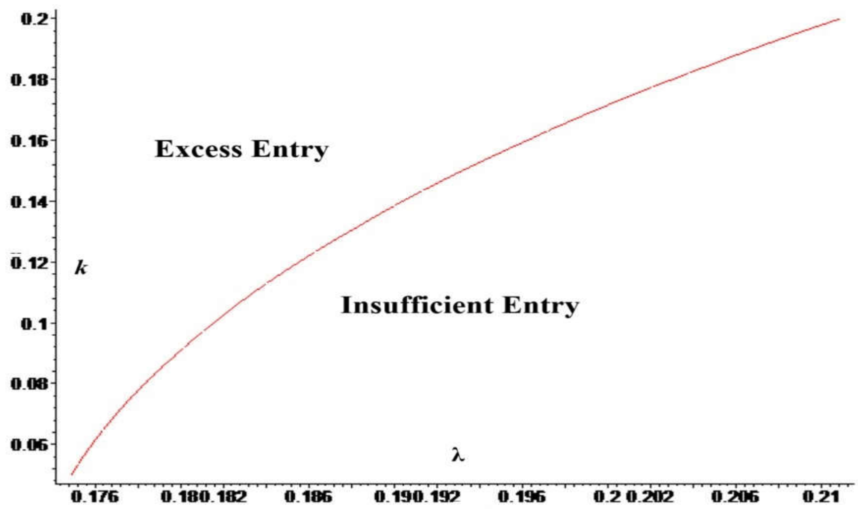

Figure 1: Association Between AI and Market Entry

Next, we can further analyze consumer welfare. Assuming $t=1$ and $k_c = k_q = k$, the consumer surplus function can be expressed as follows:

$$CS(N) = 3\frac{(1-\lambda N)(16Nk^2+3\lambda N-12)}{N(9-16Nk^2)^2} + v - c - \frac{3}{4N}. \tag{8}$$

This expression provides a way to quantify consumer surplus (CS) as a function of the number of firms (N) in the market, incorporating key factors such as the quality-improving and cost-reducing effects of AI (k), the specific cost (λ) of purchasing from the central firm. Given a fixed number of small firms, consumer surplus increases with k, that is, $\frac{\partial CS(N)}{\partial k} > 0$. This is because higher values of k lead to greater quality improvements and cost reductions, which are typically passed on to consumers in the form of lower prices or better products, thereby enhancing their overall welfare. Further comparative analysis can be conducted to examine consumer surplus, firms' profits and social welfare when N is endogenously determined. This involves exploring how the interplay between AI's effects and market entry decisions influences profits and welfare.

AI Investments for Small Firms

In addition to analyzing the impact of AI investments by the central firm, it is crucial to consider how small firms might engage in AI adoption and its implications for market structure and welfare. Small firms often face resource constraints, limiting their ability to invest in advanced AI technologies. However, when such investments are feasible, they could potentially level the playing field with the central firm by improving efficiency, enhancing product quality, or reducing operational costs. We then extend the previous framework by allowing small firms to also invest in AI, modifying the utility and profit functions accordingly. The utility for consumers purchasing from firm i $(i = 1..N)$ becomes

$$U_i = v + k_q\, e_i - p_i - t\left|x - \frac{i-1}{N}\right|, \quad i = 1..N,$$

where e_i represents the AI investment made by firm i. The profit function for small firm 1 (π_1) is given by:

$$\pi_1 = 2(p_1 - (c - k_q\, e_1))\, \hat{x}_1 - F - e_1^2/2.$$

It highlights the trade-off small firms face between higher costs of AI investment and the potential benefits of increased market share and profitability. Further analysis would involve deriving equilibrium outcomes for prices, AI investment levels, and profits. Simplifying the calculations by assuming *t=1* and $k_c = k_q = k$ for the convenience of expression here, we obtain the equilibrium expressions for AI investment by the central firm and small firms:

$$e^* = \frac{8k(3(1-\lambda N)-8k^2)}{3(9-16k^2(N+1))},$$

$$e_i^* = \frac{4k(3(1+2\lambda N)-16k^2 N)}{3N(9-16k^2(N+1))}, \quad i = 1..N.$$

AI investment levels are influenced by key factors such as the quality-improvement and cost-reduction potential, the specific cost associated with the central firm, and the number of small firms in the market. Further analysis can build on this framework to examine how these equilibrium outcomes impact consumer welfare and social welfare. It can also extend to scenarios where the number of firms is determined endogenously, exploring how AI investments shape market entry and exit.

This research can also extended by incorporating elements from the "spoke model" introduced by Chen and Riordan (2007) and the "multiple cities" model developed by Hwang and Mai (1991), with enhancements by Guo and Lai (2022). These extensions aim to enrich the analysis by introducing alternative market structures. The spoke model provides a framework for studying networked markets, which is particularly valuable for exploring interactions between central and small firms. It captures the interconnectivity of firms and consumers in a way that reflects the increasing prevalence of AI implementation. On the other hand, the "multiple cities" model offers a broader perspective on spatial competition by examining market interactions across diverse urban settings, allowing for the analysis of geographical differentiation and its impact on market outcomes.

Extensions

The extensions include AI's influence on labor markets, its role in improving productivity and reshaping workforce demands, the strategic adoption of AI in competitive markets, and its broader implications for economic growth, policy, and equity. AI investment plays a vital role in this context, particularly for improving productivity and operational efficiency. A modified Hotelling model, incorporating production and labor choices, illustrates these dynamics. Consider a large firm with an established consumer base located at one end of a linear market. Its AI investments focus on improving product quality and reducing costs to maintain loyalty while potentially attracting new consumers. Conversely, a small firm without loyal customers must prioritize AI to enhance competitiveness through cost reduction and improved service quality. However, the small firm's limited resources and lack of a loyal consumer base may hinder its ability to fully capitalize on AI investments, especially if the larger firm aggressively competes on price or quality. This asymmetry highlights how AI benefits are distributed unevenly, favoring firms with stronger initial positions.

Another extension is to building on this, network effects and two-sided markets for providing further insights into the evolving competitive landscape. Platforms leveraging network effects see their value increase as participation grows. Two-sided markets add complexity by introducing dual revenue streams—consumer payments and advertising income. AI enhances these dynamics by enabling platforms to analyze and predict consumer behavior, improving user experiences and advertising effectiveness. For instance, AI-powered recommendation systems boost user engagement, while targeted advertising maximizes returns for advertisers. These interactions strengthen the role of AI in reshaping market structures, as platforms balance consumer and advertiser needs. Firms leveraging network effects and two-sided markets can adjust pricing and investment strategies to optimize their competitive positions, with AI playing a pivotal role in improving quality and efficiency.

Demand elasticity introduces another layer of complexity to these models. Traditional assumptions of fixed demand give way to scenarios where consumer responsiveness to price and quality changes becomes a critical factor. AI's ability to enhance product quality or reduce costs can significantly shift market share in cases of elastic demand, while inelastic demand dampens such effects. Adjusting utility functions to account for demand elasticity reveals how firms strategically align AI investments with consumer sensitivities. When demand is elastic, even small quality improvements or price reductions driven by AI can substantially expand market share. In contrast, inelastic demand may lead firms to focus more on maintaining existing consumers rather than aggressively competing on price or quality. Analytical and numerical methods can be applied to evaluate these effects, providing a more nuanced understanding of AI's influence on firm strategies.

The empirical and policy implications of these findings are substantial. AI reshapes market competition by improving productivity, reducing costs, and enhancing quality. Large firms with loyal consumers are well-positioned to maximize returns on AI investments, using them to strengthen customer relationships and potentially justify higher prices if quality improvements outweigh cost reductions. Smaller firms, however, must rely on innovation and efficiency to compete, often struggling to match the capabilities of larger competitors. This can lead to market concentration, as smaller firms face challenges in sustaining profitability. On the other hand, AI's ability to lower operational costs could encourage new entrants, fostering competition. Policymakers must address this dual effect to ensure equitable growth. From a consumer perspective, AI-driven improvements benefit society by offering better products at lower prices, though these benefits are not always evenly distributed. Large firms with substantial AI capabilities are more likely to capture the gains, leaving smaller firms and consumers in less competitive markets at a disadvantage. Policymakers should promote fairness by supporting smaller firms and fostering competition through targeted initiatives and regulations. AI also transforms labor markets by creating demand for advanced technical skills while reducing the need for routine jobs. This dual effect necessitates investments in education and training programs to help workers transition into roles aligned with AI-driven industries. Innovation spillovers from large firms adopting AI could stimulate advancements across industries, but they might also widen the gap between leading and lagging competitors, creating additional challenges for smaller firms.

Conclusions

The research highlights how AI influences market competition, firm behavior, and social welfare within a spatial oligopoly framework. Large firms with greater resources benefit significantly from AI investments by enhancing product quality and reducing costs, solidifying their market positions. Smaller firms, constrained by resources, face challenges in leveraging AI effectively, leading to asymmetric competitive dynamics and potential market concentration. AI-driven quality improvements and cost reductions alter pricing strategies, market entry conditions, and consumer welfare. While AI fosters innovation and operational efficiency, it also exacerbates digital and competitive disparities, raising concerns about fairness and equity. Policymakers must address these challenges through strategies that promote inclusive growth, ensure fair competition, and balance innovation with consumer protection. The findings underline the importance of regulating AI-enabled markets to prevent monopolistic practices and excessive entry while fostering an environment where all firms can thrive. This research contributes to a deeper understanding of AI's role in reshaping traditional economic models and provides actionable insights for designing policies that maximize the benefits of AI while mitigating its disruptive impacts.

Keywords: Artificial Intelligence (AI); Spatial Oligopoly; Social Welfare; Market Structure;
Digital Disparity.

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