The Algorithmic Price: AI-Driven Pricing, Market Competition and Consumer Welfare in Digital Platform Economies

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Abstract

Pricing in digital platform economies has been transformed by artificial intelligence, enabling firms to adjust prices continuously in response to demand, supply, competitor behaviour and consumer data. This paper examines the extent to which AI-driven pricing systems have affected competition and consumer welfare. Drawing on evidence from digital retail, ride-hailing, airlines, hospitality and rental housing, it evaluates both the efficiency gains and economic risks associated with algorithmic pricing. The findings suggest these systems can improve resource allocation, expand availability and intensify competitive responsiveness. However, sophisticated price discrimination, informational asymmetry and unequal access to data and technological infrastructure may shift consumer surplus towards firms and reinforce the advantages of dominant platforms. Shared and responsive pricing algorithms may also weaken independent price competition. The paper concludes that AI-driven pricing has substantially transformed competition and consumer welfare, but whether its long-term effects are beneficial depends on effective transparency, accountability and competition safeguards.

Keywords: AI-driven pricing; algorithmic pricing; consumer welfare; digital platform economies; market competition

Introduction

Digital platform economies have transformed global commerce over the past two decades. Platforms like Amazon, Uber and online travel aggregators function as data-rich ecosystems where millions of transactions take place every day. They produce constant streams of behavioural and transactional data on a scale unmatched by any traditional market. The extent of this transformation is mirrored in market data: by 2024, four of the world's five largest corporations by market capitalisation were built on platform-based business models (Sheposh, 2023). In this environment, classical pricing and monetisation models are being replaced by versatile strategies shaped by network effects (a phenomenon where a product or service becomes more valuable as more people use it) (Garg, 2025).

The core of this transformation is the shift from fixed pricing to dynamic pricing systems, where prices change constantly based on demand, supply, consumer behaviour, competitive conditions, etc. As firms increasingly use algorithms to dynamically price products, questions arise about the implications for market efficiency and consumer welfare (Grace et al., 2025). AI has accelerated this process significantly. Businesses across industries widely adopt AI-driven pricing algorithms because they can process large volumes of data, detect trends across complex variables and automatically update prices with little to no human input (Xu et al., 2023). Such tools have become standard instruments for revenue optimisation and resource allocation in e-commerce, ride-sharing and travel services.

The growing deployment of AI pricing systems has triggered academic debate. Proponents argue that algorithmic pricing benefits markets by aligning prices more precisely with real-time demand and supply conditions. Critics, however, identify more serious economic consequences. Algorithmic pricing systems may facilitate tacit collusion, erode price dispersion and undermine traditional competitive dynamics. In addition, large platforms' data capabilities enable price personalisation and behavioural prediction with unprecedented accuracy, raising fairness concerns. These tensions make it necessary to examine the economic consequences of AI-driven pricing systems with precision. Accordingly, this research paper addresses the following research question: **To what extent have AI-driven pricing systems affected competition and consumer welfare in digital platform economies?**

The Evolution of Pricing in Digital Markets: From Traditional Pricing to AI-Driven Dynamic Pricing

Historically, businesses set prices using static methods based on historical information. The most widely used was cost-plus pricing, whereby firms calculated total production costs and added a fixed profit margin to arrive at a final price. Economists have consistently pointed to this strategy's fundamental limitations: it requires little market research and does not account for external factors such as consumer demand or rivals' pricing behaviour. Similarly, competitor-based pricing sets prices in reference to rivals' price levels, while market-based pricing relies on observed supply and demand conditions to guide decisions (Wang et al., 2024). Both approaches relied on periodically gathered information rather than continuously, making them inherently slow to respond to sudden or unexpected shifts in market conditions. The main limitation of these models is precisely this - lack of flexibility and responsiveness. In stable industrial markets, this was manageable. However, the rise of the digital economy has significantly altered how businesses set prices. This is because consumer behaviour, demand patterns and competitive conditions now change at a speed that traditional models cannot accommodate (Hassan, 2025).

These limitations have led to dynamic pricing, a strategy in which businesses continuously adjust prices in response to real-time changes in demand, supply, timing, availability and consumer behaviour. Dynamic pricing gained traction as commerce shifted online in the 1990s, allowing retailers to adjust prices rapidly based on supply, demand and competitor pricing (Biscontini, 2023). Digital platforms now use data analytics and technologies such as artificial intelligence and machine learning to deploy algorithms that analyse market conditions and predict optimal pricing (Gibson, 2024). The economic rationale for dynamic pricing is grounded in classical price theory. The price mechanism performs three primary functions in coordinating economic activity: signalling relative scarcities, rationing limited resources and providing incentives for behavioural adjustments. When demand for a good rises relative to supply, prices increase, alerting producers to expand output and signalling to consumers to consider alternatives. Viewed through this framework, responsive price adjustment improves market efficiency rather than serving as a commercially motivated imposition: higher prices during periods of excess demand allocate scarce resources to those most willing to pay, while reductions during weaker demand stimulate consumption and limit idle capacity.

As one industry analysis puts it, when implemented well, dynamic pricing can efficiently help companies and customers share value (Gibson, 2024). The airline industry was among the first to institutionalise this logic at scale. The deregulation of the airline industry in 1978 ignited the field of revenue management, with airlines adopting inventory control and dynamic pricing to optimise revenue in a more competitive environment. By the 1980s, American Airlines' SABRE system had released the industry's first comprehensive revenue management system, algorithmically optimising fare classes and pricing to maximise yields per flight (Airways Magazine, 2025). The model was later used across hospitality, entertainment and retail sectors.

Artificial intelligence has since transformed dynamic pricing by fundamentally expanding its scale, speed and analytical depth. Where earlier dynamic pricing relied on human analysts making informed decisions about the most profitable price for a product at a given time, modern AI and digital analytics software scan and interpret a larger volume of data at a much faster rate, allowing prices to reflect not just broad market movements but the purchasing behaviour of individual consumers (Biscontini, 2023). These platforms analyse vast datasets encompassing competitor prices, consumer behaviour, inventory levels and market trends to dynamically adjust prices and maximise revenue, processing combinations of variables that no human analyst could evaluate simultaneously. The scale of this shift is significant: Amazon's dynamic pricing system generates about 2.5 million price changes per day, with individual product prices adjusting as often as every ten minutes (Huzenkova, 2025). The global market for AI-driven price optimisation was valued at approximately $2.98 billion in 2024 and is projected to reach $11.74 billion by 2034 (Market.Us, 2025).

These systems have become integral to digital platform economies. Because most digital platforms operate in ever-changing industries, balancing supply and demand requires dynamic pricing systems that can respond continuously to market fluctuations (Gibson, 2024). Uber's dynamic pricing engine, for example, generates tens of millions of price decisions at the geographic unit level every minute worldwide, automatically recalibrating fares in response to real-time shifts in rider demand and driver availability (Yan et al., 2020). At this scale, manual pricing is not only inefficient but operationally impossible. AI-driven pricing represents, in this context, the technological infrastructure that makes platform markets function. Yet the same features that make these systems effective at scale - their speed, data intensity and autonomy - also generate substantial questions about their consequences for consumers and market competition, questions that the sections that follow examine in detail.

AI-Driven Pricing and Consumer Welfare: Efficiency, Price Discrimination and Information Asymmetry

So far, the paper has focused on how AI-driven pricing systems operate and the scale at which they have come to dominate digital platform economies. Evaluating these systems purely in terms of business efficiency and revenue optimisation, however, offers an incomplete account of their economic significance. A fuller assessment must also consider how these systems affect the people who ultimately transact within these markets. In economic terms, consumer welfare is not measured by firm profitability but rather as the surplus a consumer receives when the price actually paid falls below the maximum amount they would have been willing to pay, a concept that has underpinned welfare analysis since it was popularised by Alfred Marshall in the nineteenth century (Samuel et al., 2022). In the context of digital platforms, however, this narrow definition of surplus must be broadened to account for the affordability, fairness, transparency and accessibility of the pricing process itself, since the same characteristics that make AI-driven pricing efficient, namely extensive data collection, algorithmic autonomy and near-total automation from human oversight, are also the properties most likely to affect these non-price dimensions of welfare (Grace et al., 2025). This section therefore addresses a twofold debate. On one hand, AI-driven pricing can improve consumer outcomes by creating more responsive and efficient markets. On the other hand, the same systems concentrate an unprecedented degree of pricing control in the hands of businesses, raising legitimate questions about whether consumers continue to receive a fair share of the value these markets generate(Pradhan et al., 2025).

The strongest argument for AI-driven pricing rests on its capacity to improve market efficiency. This directly builds on the price theory discussed in the previous section. Because algorithms can process real-time data on demand, supply and competitor behaviour simultaneously, businesses can adjust prices with a level of accuracy that manually updated pricing methods cannot match (PwC, 2019). Machine learning models allow firms to move beyond fixed markups and instead build pricing strategies informed by continuously updated demand forecasts and price elasticity estimates (Dmytro, 2026). This capacity connects directly to efficient resource allocation: prices signal and coordinate buyers' and sellers' choices and the more accurately those signals reflect underlying scarcity, the more efficiently resources are distributed across the economy (Pradhan et al., 2025). In practice, this can benefit consumers in two ways. Dynamic systems can lower prices during periods of weak demand, since AI models are able to identify slack in the market and adjust prices downward to stimulate consumption that would not otherwise occur, while price increases during periods of high demand act as a signal that draws additional supply into the market precisely when it is needed most (Department of Computer Science, Kogi State University, Anyigba, Kogi State, Nigeria. et al., 2025). Industry evidence lends some support to the scale of these gains: research cited by Pradhan et al. (2025) associates AI-driven pricing with revenue increases of five to fifteen percent and margin improvements of up to twenty percent relative to firms using traditional pricing methods, alongside algorithmic response times measured in seconds rather than the days or weeks required by legacy systems(Pradhan et al., 2025).

This efficiency argument can be tested directly against Uber's surge pricing system, one of the most extensively studied applications of AI-driven dynamic pricing in a consumer-facing market. Ride-hailing platforms face a structural problem: demand for rides fluctuates constantly and unpredictably throughout the day, while the number of drivers available at any given moment is comparatively fixed and slow to adjust (Cohen et al., 2016). When demand rises sharply, for example during rush hour, in poor weather or at a large public event, the number of riders seeking a trip can quickly exceed the number of available drivers, resulting in shortages and long wait times. Uber's pricing algorithm responds to this imbalance by automatically raising prices in the affected area. This mechanism serves two functions at once: rationing scarce rides to the riders who value them most, while the higher fare also incentivises more drivers to get on the road, increasing supply exactly where and when it is needed.

Empirical research strongly supports the claim that this mechanism improves overall consumer welfare. In one of the most cited studies on the subject, Cohen et al. (2016) used almost fifty million individual Uber sessions to estimate that UberX generated close to 2.9 billion dollars in consumer surplus across four major American cities in 2015 alone, equivalent to roughly 1.60 dollars of surplus for every dollar consumers actually spent, a figure the authors extrapolated to nearly 6.8 billion dollars nationally. More recent structural research published in Econometrica reaches a similar conclusion: relative to a counterfactual in which Uber set a single uniform price, surge pricing was found to increase total welfare by just over two percent of gross revenue, with almost all of the gain concentrated on the rider side of the market even as driver earnings and platform profit fell slightly (Castillo, 2025). These findings suggest that although consumers pay more during surge periods, dynamic pricing expands ride availability while allowing Uber to charge lower baseline prices during normal demand than it otherwise could (Knowledge at Wharton, 2016).

This evidence, however, must be weighed against research and public criticism questioning whether these gains are distributed fairly. Because surge multipliers can raise fares to several times their baseline level in the absence of a regulatory cap, critics have described the practice as a form of price gouging rather than efficient allocation and several cities, including Honolulu, Manila, New Delhi and Singapore, have introduced caps or outright bans on surge pricing in response. The evaluative question this case raises is therefore not simply whether surge pricing increases efficiency in aggregate, since the evidence broadly suggests that it does, but whether raising the price of an essential service exactly when substitutes are least available is an acceptable cost of that efficiency, particularly for the riders who have the fewest alternatives available to them at the moment they need a ride most.

Beyond surge-based dynamic pricing, AI has also transformed the older economic practice of price discrimination, defined as the practice of charging different consumers different prices for an identical good or service based on their individual willingness to pay . Price discrimination itself is not new: discounts for senior citizens and students, along with higher fares for last-minute business travel, are long-standing examples that most consumers have come to accept (Furman & Simcoe, 2015). What AI has changed is the precision and scale at which firms can identify willingness to pay. Because platforms can now draw on granular data covering browsing behaviour, purchase history, geographic location, device type, etc., machine learning models can segment individual consumers, rather than broad demographic groups and generate a tailored price for each one (PwC, 2019). The consumer welfare implications of this shift cut in two directions. Personalised pricing can generate genuine benefits when it extends targeted discounts to price-sensitive shoppers who would not otherwise complete a purchase, effectively widening access to goods and services beyond what uniform pricing would allow, a possibility acknowledged even in early government analysis of the practice (Furman & Simcoe, 2015). At the same time, the same data and modelling capability that enables these discounts also lets firms identify consumers with the highest willingness to pay and charge them more, shifting surplus toward the firm rather than creating new value overall (Pradhan et al., 2025). Regulators have increasingly focused on this second possibility: the United States Federal Trade Commission's ongoing study into what it terms surveillance pricing found that firms and the data intermediaries that serve them routinely draw on information as specific as a consumer's precise location or their mouse movements on a webpage to help set individualised prices (FTC, 2025).

The airline and hotel industries illustrate this tension particularly clearly, since both combine largely fixed, perishable capacity with highly variable demand. Airlines have recently begun using generative AI to forecast demand and adjust fares in near real time. Delta Air Lines, for instance, has partnered with the AI firm Fetcherr to price a growing share of its domestic fares using models that account for factors such as cabin class, booking timing and historical demand patterns, with plans to expand the system from a small initial share of flights to roughly twenty percent of fares (Williford et al., 2026). Delta has stated publicly, including in written responses to members of Congress, that it does not use and does not intend to use any pricing model that targets individual customers based on their personal data, describing its system instead as an extension of the dynamic pricing airlines have used for decades, adjusted for demand, fuel costs and competition rather than individual profiles (Reuters, 2025). Even so, the announcement triggered considerable scrutiny from lawmakers and consumer advocates, who argued that the complexity and opacity of these systems make such assurances difficult for outsiders to verify. As one expert interviewed on the matter put it, the central problem is not price variation itself, since discounted fares for students or seniors are broadly accepted, but the lack of transparency surrounding how algorithmic prices are generated, leaving consumers unable to know whether a quoted fare reflects market conditions or something more specific to them (Kuzub, 2025).

A comparable pattern has emerged in the hotel sector, where AI-based revenue management systems forecast demand and adjust room rates to prevent unsold inventory, with providers reporting measurable gains in forecasting accuracy and revenue. Yet the same systems have generated consumer backlash when their outputs appear arbitrary or discriminatory. For example, a widely reported 2020 case in which a major online travel agency charged different prices for the same hotel room prompted public accusations of a loyalty tax, illustrating how quickly efficiency gains can be overshadowed by perceptions of unfairness once consumers suspect identical products are being priced differently without explanation (Wang, 2026). In response to controversies like this across the travel sector, regulators in several jurisdictions have begun requiring greater disclosure rather than banning algorithmic pricing outright (Williford et al., 2026). New York State now requires businesses to disclose when a price has been set using a consumer's personal data, Maryland has restricted certain surveillance pricing practices outright and the Federal Trade Commission has drawn an explicit distinction between dynamic pricing that responds to market-wide conditions, which remains widely accepted and personalised pricing that responds to the characteristics of an individual consumer, which is now the primary focus of regulatory concern (FTC, 2025).

Underlying each of these cases, whether surge pricing, personalised discounts or airline and hotel fares, is a common structural feature. AI-driven pricing systems have widened the gap between what companies know about consumers and what consumers know about how their own prices are set (Dmytro, 2026). Firms can increasingly build a precise understanding of individual behaviour, preferences and willingness to pay by drawing on continuously updated behavioural and transactional data, while the average consumer typically has little visibility into which of their own characteristics, if any, informed the price they were shown. Gerlick and Liozu (2020), drawing on earlier work by Ezrachi and Stucke, argue that as the distinction between broad dynamic pricing and individually personalised pricing continues to blur, firms are able to use their data advantage to widen this informational gap deliberately, raising the practical cost to consumers of ever discovering what a genuine market price would have been. This dynamic helps explain why regulatory attention has increasingly shifted from price variation itself to disclosure and explainability (Gerlick & Liozu, 2020).

Taken together, the evidence in this section suggests that AI-driven pricing systems can improve consumer welfare by allocating scarce goods and services more efficiently and, in some cases, by extending access to consumers who would otherwise be priced out entirely. These benefits, however, are conditional, not automatic. They depend on whether the informational advantage that AI grants to businesses is used to expand the overall value available to consumers or simply to capture a larger share of value that already exists. This distinction is central to the research question guiding this paper, since it suggests that the extent to which AI-driven pricing has improved competition and consumer welfare in digital platform economies cannot be judged by efficiency gains alone, but must also depend on whether consumers continue to receive fair, transparent and accountable treatment as these systems become further embedded in digital markets.

AI Pricing and Competition: Market Power, Platforms and Algorithmic Control

Having considered AI-driven pricing primarily from the perspective of consumers, it is vital to acknowledge that its effects also extend to the competitive structure of digital markets. Ordinarily, competition incentivises firms to lower prices, improve quality and innovate to attract consumers. Algorithmic pricing could strengthen this process by letting firms respond more quickly to market conditions. Pricing algorithms can continuously monitor competitors and automatically adjust prices, replacing the slower decision-making associated with traditional pricing. Research on major online retailers has found that firms with faster pricing technologies tend to charge lower prices, suggesting that greater responsiveness can intensify price competition (Brown & MacKay, 2022). The Canadian Competition Bureau similarly argues that algorithmic pricing may improve efficiency and lower barriers to entry by allowing new firms to use sophisticated pricing strategies to compete with established businesses (Government of Canada, 2025).

Amazon Marketplace illustrates these potential benefits particularly clearly. Amazon operates as both a retailer and a marketplace that connects large numbers of third-party sellers, creating an environment in which multiple firms frequently compete to sell identical products (Chen et al., 2016). Consequently, many sellers use automated repricing systems to monitor competitors and respond through strategies such as matching or undercutting rival prices (Brown & MacKay, 2022). Chen et al.'s (2016) empirical analysis of Amazon Marketplace found highly dynamic pricing behaviour and identified sellers whose prices appear to be determined algorithmically. Such technology can therefore reduce the disadvantage faced by smaller sellers who lack dedicated pricing teams, since automated tools allow them to respond to competitors at a speed that previously required substantially greater resources.

However, faster responses do not necessarily produce stronger competition. The same responsiveness that enables sellers to undercut competitors may also reduce incentives to cut prices. If one seller knows a competitor's algorithm will immediately match or undercut any price cut, lowering its own price becomes less profitable because any resulting increase in market share may disappear almost immediately (Brown & MacKay, 2022). This concern is supported by empirical research beyond e-commerce; research on Germany's retail gasoline market found that algorithmic pricing adoption could produce higher margins, demonstrating that automation does not automatically intensify price competition (Assad et al., 2024). More broadly, AI pricing may itself create barriers to entry because sophisticated systems depend upon computational resources and large datasets that established firms are better equipped to possess. Competition may therefore become increasingly unequal when firms compete not only on price but also on the quality of the data and algorithms available to them.

Amazon further demonstrates this tension as it is simultaneously a participant in and an operator of the marketplace. This gives the platform considerable influence over the environment within which third-party sellers compete (Chen et al., 2016). More importantly, the FTC’s case against Amazon illustrates how algorithmic responsiveness can potentially be exploited rather than merely accommodated. Amazon's discontinued Project Nessie reportedly tested whether competing retailers would follow Amazon's price increases; Carnegie Mellon (2023) researchers explain that sophisticated algorithms can learn that competitors using simple matching rules will respond to price increases by raising their own prices, producing higher prices without explicit communication between firms. This highlights a central problem with algorithmic competition: firms may act independently, yet their automated systems can produce outcomes that resemble coordinated pricing.

Similar concerns have also emerged around shared pricing algorithms, including systems used in rental housing. Competition authorities increasingly recognise that when competitors rely on common algorithms and shared competitive data, independent pricing decisions may be constrained, creating conditions in which prices move together rather than being independently contested. The RealPage controversy therefore shows how the competitive implications of algorithmic pricing extend beyond online retail: automation can transform how competitors set and respond to prices, raising concerns that shared pricing systems may weaken independent price competition (Reeves, 2026).

Ultimately, AI-driven pricing has made competition more data-driven and faster, but not necessarily more competitive. Its impact depends on who controls the algorithms, data and digital infrastructure. These technologies may give smaller firms tools to compete more effectively, but they may also reinforce the advantages of dominant platforms and reduce incentives for real price competition. AI pricing has therefore dramatically changed the nature of competition. The degree to which this change is good for markets depends less on automation per se than on the competitive structure in which it occurs.

Regulation, Governance and the Future of AI Pricing

AI-driven pricing has created new challenges for both producers and consumers. OECD (2025) and Canadian Competition research (Marty & Warin, 2025) note that algorithmic pricing can promote efficiency while also enabling collusion and manipulation, so the real question is not whether to remove it from digital markets, but how to preserve innovation alongside consumer and competitive protection.

Traditional pricing decisions could usually be explained through observable factors such as costs, demand and competitor behaviour. AI-driven systems complicate this, since they draw on continuously updated, often proprietary data and generate outcomes even the businesses deploying them may struggle to justify. A Brookings Institution analysis describes online pricing as fundamentally imbalanced, since sellers now know far more about buyers than buyers know about how prices are set (West, 2016). A 2026 U.S. House Oversight Committee investigation labelled these systems a black box, a term echoed by respondents to a parallel Canadian consultation and, in a milder form, by Forbes commentary describing consumer unease even when pricing shifts are openly explained (Williford et al., 2026).

Algorithmic accountability raises a related question: who bears responsibility for harmful pricing outcomes, the company, the developers who built the system or the algorithm itself? Competition law was built around human coordination and a Government of Canada (2026) consultation found that tacit collusion between algorithms often escapes existing rules, which require proof of a meeting of minds that autonomous systems do not leave behind. The FTC's case against Amazon, reported by the Washington Monthly, tests this gap directly: the agency alleges Amazon's algorithms lifted market-wide prices by reacting to rivals without explicit agreement, a dynamic economists Zach Brown and Alexander MacKay call algorithmic coercion and a federal judge let the case proceed, ruling that such conduct can violate antitrust law even without collusion (Mitchell, 2026).

Several U.S. states now require or restrict algorithmic pricing directly: New York mandates disclosure when a price reflects a consumer's personal data, while California's amended Cartwright Act makes it unlawful to use a shared pricing algorithm to restrain trade or coerce rivals into matching a price (Yavorsky et al., 2026). In the European Union, the Digital Markets Act, Digital Services Act and AI Act impose overlapping transparency and data obligations and the United Kingdom's Competition and Markets Authority can now test pricing algorithms directly (Weiss, 2026). The OECD notes that most G7 authorities remain at an exploratory stage, gathering evidence (OECD, 2025).

The central challenge going forward is balance. Legal and economic commentators increasingly argue that algorithmic pricing tools are not inherently anticompetitive and that regulatory efforts should focus on intent, effect and transparency rather than blanket restriction, since overly rigid rules risk discouraging innovations that genuinely benefit consumers. The conclusion now addresses whether AI-driven markets can remain competitive, transparent and beneficial while continuing to innovate.

Conclusion

This research paper examined the extent to which AI-driven pricing systems have impacted competition and consumer welfare in digital platform economies. Digital platforms have shifted decisively from static, cost-based pricing to continuous, data-driven pricing systems that can adjust in real time to shifts in demand, supply and consumer behaviour.

Regarding consumer welfare, the impact of these pricing systems is mixed; greater responsiveness can improve resource allocation, availability and affordability under certain market conditions. However, increasingly sophisticated price discrimination and limited transparency can allow firms to capture a greater share of consumer surplus, meaning the greater efficiency does not necessarily translate into greater consumer welfare.

The impact on competition follows the same pattern. Algorithmic pricing can intensify rivalry by enabling firms to respond rapidly to competitors while giving smaller sellers access to more sophisticated pricing capabilities. However, depending on the data, algorithms and digital infrastructure, they may reinforce the advantages of dominant platforms, while shared or responsive pricing algorithms can weaken independent price competition.

These tensions make effective regulation increasingly important. Regulation must improve transparency and accountability and prevent algorithmic systems from facilitating anti-competitive outcomes without restricting the efficiency and innovation they can generate.

Overall, AI-driven pricing has impacted competition and consumer welfare to a substantial extent, but its effects remain conditional. Whether its long-term impact is ultimately beneficial will depend on whether the markets and regulators can preserve its efficiency gains while limiting excessive market power, protecting genuine competition and ensuring fair treatment of consumers

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