Section I

연구논문

The Economics of Data

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This paper offers a survey of the recent literature related to the economics of data. In particular, we look at how data can confer market power and facilitate collusion, and consider some of the privacy implications of data ownership.

Keywords: Network effects; platforms; market power; price discrimination; privacy
JEL codes: D43; L13; L14; L41

1. Introduction

During the twentieth century, developed economies have been through a major transformation, with the emergence of information, data, and digitization. This transformation has had significant implications for the functioning of markets. In this paper, we explore three of those implications: market power; collusion; and privacy.

Market power: Firms that rely on data often benefit from increasing returns to scale. The more data they have, the better they become at creating value for consumers. A search engine like Google is able to offer relevant search results because of all the search queries it receives. One might then wonder whether the

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presence of increasing returns creates barriers to entry that prevent new and innovative firms from disturbing the status quo. Furthermore, platforms that once acted as pure intermediaries can use data to learn and decide whether or not to enter and compete with the sellers it hosts. This can have effects on incentives to innovate and product offerings.

Collusion: Market interactions between competitors are often repeated over time. This repetition can sometimes lead to collusion, whether implicit or explicit. Various pricing strategies, such as ““grim-trigger”’ and ““tit-for-tat”’, allow for collusion to happen. In the era of big data, a lot of the pricing strategies are left to machine learning and AI algorithms. The question as to whether such algorithms can learn to collude is therefore important for consumer welfare.

Privacy: Unlike physical goods, data can be used simultaneously by many firms. Moreover, it is often the case that data from one consumer reveal information about others. This leads to the question of whether data is shared optimally between firms, and whether privacy is sufficient.

2. Data and Market Power

2.1 Increasing Returns and Instability

A key assumption of classical economics is that of non-increasing returns to scale: when producing, firms eventually run into limitations, such that it becomes more costly to produce additional units. This assumption of non-increasing returns to scale has allowed economic models to offer clear predictions about important economic outcomes, such as equilibrium prices and quantities, competition, or market shares.

From the onset of the early 80s, however, some markets started exhibiting increasing returns to scale. For example, the DOS operating system had an early advantage compared to Apple's Mac computers, which encouraged software developers to focus on DOS's platform, re-enforcing its dominance.

In two seminal contributions, Arthur (1989, 1996) describes the characteristics of an industry exhibiting increasing returns: "market instability […], multiple potential outcomes […], unpredictability, the ability to lock in a market, the possible predominance of an inferior product, and fat profits for the winner."

One important source of increasing returns is data. Consider for example the search engine market. The more data about searches Google has, the better it becomes at offering relevant search results. The more a social network knows about its users, the more relevant it can be with its recommendations and sponsored content.

However, as Arthur points out, markets with increasing returns are also characterized by instability. Technology comes in successive waves, which means that losers can become winners, winners can become losers if complacent, and market participants might not be able to anticipate what technology will come next and replace them.

As soon as the Blu-ray came out as the winning standard from its war with the HD-DVD format, streaming started emerging, impeding this success. Similarly, the history of social networks suggests turnover and instability (see Tucker, 2018). Friendster, one of the first successful social networks, was quickly replaced by MySpace, which then declined while users migrated to Facebook. While Facebook successfully identified potential threats, as can be seen by the purchase of Instagram for the unprecedented price of $1 billion, its dominance is now dwindling, with the appearance of new players such as Snapchat or TikTok.

Even the giants of the tech world, Google and Apple, both failed at their social network attempts. Google was not able to successfully leverage its large Gmail user base to develop Google Plus, its Facebook competitor, and Apple failed at making iTunes (the biggest online music store) social with Ping in 2012.

Finally, Google Search, the dominant search engine, is now facing a new threat from OpenAI's chatbot, ChatGPT. ChatGPT has seen the fastest adoption rate in the Internet space, reaching 100 million users two months after its launch. By comparison, it took TikTok nine months to reach this milestone and more than two years for Instagram.[2]

2.2 Competitive Advantage and Market Power

In the light of increasing returns and instability, is data an important source of market power? Before answering, we may first question whether market power has increased in recent history.

Tobin's *Q* offers a measure of corporate rent. It is the ratio of the firm's market value and its replacement cost of capital. A ratio above 1 suggests an obvious way for new entrants to make money: purchase capital to produce the same goods as the market incumbents. Such entry would increase the supply of goods, reducing prices, and the value of firms. Eventually, in a competitive market, a ratio of 1 is expected.

US data however suggests a value of Tobin's *Q* significantly above 1. Peters and Taylor (2017) use firm-level data from publicly traded U.S. corporations and find average values of *Q* ranging from 0.5 to 3 over the period 1975-2015, with a *Q* going up to 6 for the 90th percentile group.

The existence of such rents should attract new competitors unless significant barriers to entry are in place. Network externalities and access to data can be the source of such barriers to entry. Kwon et al. (2023) look at concentration in U.S. markets over the past 100 years, finding that corporate concentration has increased over the past century and that one potential reason for this is the rising technological intensity.

De Ridder (2019) shows that the rise of intangible inputs, such as software and data, reduces marginal costs and raises fixed costs. This gives firms with high intangibles a competitive advantage and deters other firms from entering. Those firms then reinforce their market power by continuing to invest in R&D.

Similarly, Eeckhout and Veldkamp (2022) consider a model in which data

(2) See Milmo and Agency (2023)

pushes firms to invest and produce at a lower marginal cost and a larger scale. In their model, there is uncertainty about consumer demand, and data can help resolve this uncertainty. They find that data affect markups through two channels. First, data reduces uncertainty about consumer demand, which encourages firms to produce more. This leads to more competitive markets and lower markups. However, data and a reduction of uncertainty also push firms to invest more in R&D and reduce marginal costs. This makes it more difficult to compete with other firms and raises markups. Finally, data push firms to shift their production to high-demand goods, again raising markups.

Rather than the reduction of uncertainty, Hagiu and Wright (2023) look at how data can help companies improve their products. They consider two types of learning: across-user learning and within-user learning.

First, with across-user learning, companies pool different customers' data to improve the experience for all users. This is the case, for example, with search engines, text-processing applications, and autonomous vehicle systems. Next, with within-user learning, firms learn from a specific customer's repeated usage to improve its experience. This is for example the case of health and fitness trackers, which provide personalized advice. Finally, many firms also combine both across and within-user learning. This is for example the case of services that offer recommendations, such as TV/movies and music streaming services.

The key feature of learning, whether across or within users, is that it increases consumers' willingness to pay. By developing a model of dynamic competition and learning, they find that the winning firm has higher profits when learning is across users rather than within users. The reason is that within-user learning generates switching costs, which consumers anticipate, leading to more competitive pricing.

They also find that providing more data to the losing firm increases consumer surplus, suggesting that data-sharing policies might be welfare-enhancing.

2.3 Data, Entry, and Competition

Traditionally, platforms have been an intermediary through which two sides of a market interact. For example, Amazon has been a platform through which buyers and sellers interact; Google Search has been a platform through which advertisers can reach consumers who search the Internet. Through this role as platforms, both Amazon and Google have gathered a significant amount of data about consumers, allowing them to compete on their platforms. Amazon is now selling its own products, through brands such as "Amazon Basics" and "Amazon Essentials", along with products of other brands. Google is often advertising its own products, such as Google Chrome, on its homepage. Both Google and Apple are offering their own apps on the Play Store and App Stores, apps that compete with the offering of third-party developers.

Hagiu et al. (2022) consider a platform that can operate under three different business models: the marketplace mode, in which it only acts as an intermediary between two sides of a market; the seller mode, in which it only sells its own products and not the ones of competitors; and the dual mode, in which it operates both as a marketplace and a seller. They find that the dual mode is always preferred to the marketplace mode and that a ban on the dual mode would result in a lower consumer surplus. This is because of the strategic response of the platform, which could be to switch to the seller mode, effectively reducing competition.

When the dual mode is possible, the issues of imitation and steering arise. Amazon can imitate products that are popular, and steer consumers away from competitors' offerings when displaying search results. Similarly, Google can identify which apps are popular in its Play Store and develop a similar offering. When taking imitation and steering into account, Hagiu and Wright still find that a ban on dual mode has a negative impact on welfare. The effect of banning both imitation and steering on welfare is ambiguous, depending on whether the platform reacts by choosing the dual mode or the seller mode.

Anderson and Bedre-Defolie (2021) uncover another negative effect of the dual mode, in a setting where the platform is a price leader and third-party sellers are horizontally differentiated. Dual mode leads to higher platform fees than seller mode, which reduces the number of third-party offerings, thereby reducing variety.

Zhu and Liu (2018) conduct an empirical analysis of Amazon's entry patterns. They find that Amazon is more likely to enter a product space when those products have higher sales and better reviews, and less likely to enter a product space if it requires greater seller efforts to grow.

Madsen and Vellodi (2022) look at the effect of entry from platforms on third-party sellers' incentives for innovation. Third-party sellers can develop a new product to sell on the platform but face significant uncertainty. The platform can learn about this uncertainty by observing the outcomes of the third-party seller, and then deciding whether or not to imitate. They find that regulation that bans the platform from using its own marketplace data can either stifle or stimulate innovation, depending on the nature of innovation. In particular, in markets for incremental products, such a ban may make the platform behave more competitively, reducing third-party sellers' incentives to innovate.

3. Collusion

Interactions between firms are often repeated over time. This leads to the possibility of collusion through strategies such as grim-trigger, in which deviation from a collusive outcome is punished by a price war, or tit-for-tat, in which firms imitate the behavior of their rivals. The scope for collusion is wide: indeed, the celebrated Folk theorem states that any payoff profile, provided it is individually rational, can be the outcome of equilibrium in the repeated game.

The rapid rise of digitization and big data, and the emergence of pricing algorithms, have raised new concerns when it comes to collusion. As mentioned, pricing algorithms such as grim-trigger or tit-for-tat have already been known to enforce collusive outcomes. With big data, pricing algorithms now often rely on machine learning and artificial intelligence and might facilitate collusion.

Factors that have been known to facilitate collusion include market concentration, product homogeneity, firm symmetry, and patience. For example, collusion is more difficult to sustain when there is a larger number of firms, as monitoring deviations becomes more difficult. Algorithms can help alleviate this problem, as their speed in collecting and analyzing data facilitates monitoring.

For collusion to hold, players must sufficiently care about the future, so that current gains from a deviation are outweighed by future losses from a price war. Alternatively, the frequency with which firms interact must be sufficient. By allowing timely adjustment of prices, and dramatically increasing the speed at which firms make business decisions, algorithms have contributed to a dramatic increase in the frequency of interactions between firms, again facilitating collusion.

It is important to note that there is a difference between illegal (or explicit) collusion and tacit collusion. When it comes to illegal collusion, firms must have entered explicit agreements to suppress competition, through direct communications. Proof of such agreements can then lead to criminal sanctions. On the other hand, tacit collusion, which is the ability of firms to sustain collusive prices without explicit agreements but through equilibrium strategies, is not illegal.

Algorithms allow firms to reach such collusive prices without having to enter into explicit agreements more easily. They do so by enhancing monitoring, reacting swiftly to changes in market conditions, and offering credible signals that one is willing to maintain collusive prices.

Finally, a lot of algorithms now rely on artificial intelligence and machine learning. Recent research suggests that such AI algorithms are capable of reaching collusive outcomes. (See for example Calvano et al., 2020 and Calvano et al., 2020.)

4. Privacy

Privacy is a broad concept with many facets. Warren and Brandeis (1890), in one of the most influential essays in the history of American law, define privacy as the “right to be let alone’’. Posner (1978) views privacy as encompassing many features, such as the right to be free from invasions into one’s solitude, the right to be free of publicity which casts one in a false light in the public eye, or the right to control the use of one’s name or image for commercial purposes.

Economists interested in digital markets often think of privacy in terms of informational privacy: “personal information and the problems and opportunities created by its collection, its processing, its dissemination, and its invasion.” (Brandimarte and Acquisti, 2012.)

With the rise of digital platforms, data collection, and commercialization has grown at a tremendous pace. A lot of this data about individual consumers can be of a sensitive nature: it can include preferences, location data, health data, information about friends and social networks, or political views. Although sensitive, this data is a necessary input for Internet platforms, allowing them to offer more relevant search results, recommendations, and ratings, or targeted advertisements. The later is particularly important for the modern Internet, financed almost exclusively through advertising.

In what follows, we explore the connection between data and privacy through the lens of price discrimination, advertising, and data externalities

4.1 Privacy and price discrimination

Markets with heterogeneous consumers often feature asymmetric information: firms do not know consumers’ values. Tracking, for example through Internet cookies, or the observation of past purchases, has helped reduce this asymmetry. As firms learn about consumers’ values, they can then personalize the prices they offer over time, and consumers have displayed a higher willingness to pay may end up facing higher prices in the future. However, consumers may anticipate this ratcheting of prices, and thus be more cautious when revealing their private information. This could be done by taking additional measures to protect their anonymity, or, more drastically, delaying their purchases, eventually leading to a loss in revenues.

An early model that shows the negative effect of tracking is Hart and Tirole (1988). They consider a monopolist selling a durable good, facing one buyer with a private value, in finite time. Without commitment from the seller, the optimal price path for selling the good displays Coasian dynamics, declining over time, while the rental price of the good shows a ratcheting, increasing over time. However, when the horizon becomes arbitrarily large, the price offered in most periods is the lowest price possible, and the seller's profits are lower than in the sales model. Because of the inability to commit, and because consumers strategically anticipate the monopolist's behavior, prices are pushed downward, and profit is low.

Villas-Boas (2004) considers an infinitely lived monopolist and facing overlapping generations of consumers. The monopolist can offer different prices to previous consumers and new ones. In equilibrium, prices fluctuate because of price discrimination, but the monopolist would reach a higher profit if it could commit not to price discriminate. This loss of revenue occurs because consumers who face a high price can decide to delay their purchase in order to buy at a lower price in the next period. A similar result is found by Acquisti and Varian (2005) using a two-period model.

More recently, Bonatti and Cisternas (2020) consider a long-lived consumer interacting with a series of firms over time. Past purchases are aggregated in a score, which is a proxy for willingness to pay. Strategic consumers reduce their demand to reduce their score, which in turn lowers equilibrium prices. Thus, the ability that firms have to track consumers and price discriminate leads yet again to a negative outcome for firms.

Turning to models of competition between firms, a novel issue arises: poaching. Using past information and price discrimination, firms can target their competitor's consumers more aggressively. Villas-Boas (1999) considers a duopoly with infinitely lived firms and overlapping generations of consumers, in which firms have information about their customers' past purchases, allowing them to set a different price for those previous customers than for new customers. He finds that consumer poaching lowers equilibrium prices. Fudenberg and Tirole (2000) also look at customer poaching in a duopoly setting, albeit within a two-period model. They find that firms offer too many discounts to their rival's customers, and that switching is inefficient.

Price discrimination based on past purchases may have occurred at Amazon. This is recounted in Streitfeld (2000). All started with a consumer clearing his browser cookies and noticing that the price of a particular DVD was lower than when logged in to his Amazon account. He shared this observation on forums, and other Amazon customers noticed similar price disparities. Discontent grew, and Amazon issued an apology and offered refunds to more than 6,000 customers. They nevertheless denied they were using consumer data to price discriminate, instead saying that the price variations were purely random, for the purpose of demand discovery.

4.2 Advertising

As seen above, using tracking information to personalize prices is not necessarily a good strategy. Moreover, a lot of services in the digital economy are offered at a price of zero - see for example Facebook, Instagram, Twitter, and Gmail, which are all available for free. Personalized pricing may not be of practical relevance. Instead, lower tracking costs have favored the emergence of personalized advertising, in the hope of increasing its profitability. Ad sales represent more than 85% of Alphabet's (Google) revenue.

While personalized advertising may have privacy implications, most economic research has focused on measuring its efficacy. Lewis and Reiley (2014) conducted a randomized experiment for a major US retailer on 1.6 million customers visiting Yahoo!. By matching Yahoo! users with the retailer's database, they were able to accurately measure the effect of an ad campaign, finding that it was profitable and increased sales by 5%, mostly from offline purchases.

Blake, Nosko, and Tadelis (2015) perform similar randomized experiments for eBay and its advertising strategies. They find that brand key advertising is unnecessary, as most of the foregone click traffic was captured by natural search traffic. Moreover, they found that advertising for non-brand terms was effective for new or infrequent users, but those represent such a small fraction of eBay's clientele that the ad campaign was not profitable. This suggests that one of advertising campaigns' main functions is to introduce a brand to those who do not know it, or who do not purchase from it often.

Goldfarb and Tucker (2011) look at the effectiveness of display advertising (within a website) based on two criteria: matching with the website content, and obtrusiveness. They find that both independently increase purchase intent. However, when used in combination, these two strategies are ineffective and relate their result to privacy concerns.

Shiller, Waldfogel, and Ryan (2018) look at the effect of ad-blocking software and find that the widespread use of ad blockers may decrease the quality of websites on the advertising-supported Internet. To avoid any reversed causality issue (people use ad blockers because the quality of websites is low), they use the geographic proximity of users to the source of ad blockers as an instrument. This is done by looking at the geographical patterns of the search term "Adblock Plus" on Google between 2011 and 2016.

4.3 The digital privacy paradox

While data about consumers appear to be very valuable for companies, consumers are easily willing to relinquish their private information. Athey, Catalini, and Tucker (2017) conduct a field experiment on MIT students which is now often referred to as the "digital privacy paradox." First, the experiment asks students to reveal information about their social networks. They find that small incentives, such as a pizza, can have big effects on the disclosure of private information. Next, the experiment offers some Bitcoins to the students, along with various suggestions regarding how to ensure the privacy of their transactions. They find that randomization had a large impact on the steps students would take to protect their privacy. There thus seems to be a discrepancy between how firms value the private data of consumers, and the steps consumers are willing to take to protect such data.

4.4 Data externalities

A very recent series of papers have started to explore the correlations within consumer data, in the form of externalities. In this literature, data about one user also reveals data about other users. This is often the case when thinking of social networks. Such externalities can then lead to too much data sharing compared to the social optimum. See for example Choi et al. (2019), who consider the case of a monopoly market, or Acemoglu et al. (2022), who also consider the case of platform competition, which can exacerbate the problem of excessive data sharing.

Bergemann et al. (2022) suggest that such data externalities can explain the discrepancy between how much consumers value their privacy and how much firms value data. They find that small compensations can induce consumers to reveal their private information and that privacy regulations must focus on the segmentation of consumers at the group level rather than being concerned about personalized prices at the individual level.

Jones and Tonetti (2020) consider the public good nature of data, which, unlike physical goods, is nonrival. As a result, wider usage of data, and hence data sharing between firms, may be socially optimal, even when taking privacy considerations into account.

Ichihashi (2021) also considers a setting with data externalities, as information about some consumers reveals information about others. The paper characterizes the optimal allocation of data, and how a firm collects consumer data. Data externalities can be beneficial or harmful to consumers, but a firm choosing what information to collect will lead to too much data collection and harm consumers.

5. Conclusion

The emergence of digitization and big data has transformed how markets function. Data can be a source of market power and facilitate collusion while having important implications for privacy. In the light of such transformation, policymakers must evaluate whether the regulatory and pro-competitive tools put in place since the late 19th century are still relevant in the digital age.

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