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ARTIFICIAL INTELLIGENCE AND ANTITRUST LAW: A PRIMER

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ABSTRACT

Artificial intelligence (AI) embodies rapidly evolving technologies with great potential for improving human life and economic outcomes. However, these technologies pose a challenge for antitrust enforcers and policymakers. Shrewd antitrust policies and enforcement based on a cost-benefit analysis support a thriving pro-innovation economy that facilitates AI development while mitigating its potential harms. Misguided policies or enforcement can stymie innovation, undermine vigorous economic competition, and deter research investment. This primer is a guide for policymakers and legal scholars that begins by explaining key concepts in AI technology, including foundation models, semiconductor chips, cloud computing, data strategies and others. The next section provides an overview of US antitrust laws, the agencies that enforce them, and their powers. Following that is a brief history of US antitrust law and enforcement with a focus on the consumer welfare standard, its basis and benefits, and the flaws underlying recent calls by the Neo-Brandeisian movement to abandon it. Finally, the primer outlines the law and a procompetitive, pro-innovation policy framework for approaching the intersection between AI technologies and evaluating horizontal and vertical mergers, policing anticompetitive monopolization practices, price fixing and algorithmic collusion, and consumer protection issues.

JEL codes: K21, K24, L41, L42, L51

Keywords: artificial intelligence, antitrust, competition law, law and economics, vertical restraints, mergers and acquisitions, tech, software, cloud computing, algorithms, algorithm, large language model, collusion, monopolization, monopoly, consumer welfare, consumer protection, data, Federal Trade Commission, Department of Justice, policy, economics of regulation, predatory pricing, price fixing, refusal to deal, litigation

INTRODUCTION

Artificial intelligence (AI) refers to a slew of new technologies that automate or replicate cognitive functions of the human mind through mechanisms like machine learning.[1] AI projects impact a range of diverse and economically important industries, with applications ranging from the replication of human reasoning, intelligence, and discernment, to simply automating specific complex tasks. The vast majority fall under the latter category.[2] AI facilitates these functions through increased analytical speed and scale of action, thereby contributing to a range of applications that improve human life and economic development.[3] These include finding and facilitating the development of new drugs, aiding in medical diagnosis and treatment, assisting educators in developing and running programs, generating pictures and search results for research queries, and many more. AI poses a challenge for courts in the United States, as well as enforcement agencies like the Federal Trade Commission (FTC) and the Department of Justice (DOJ). Enforcers and policymakers must prudently weigh the benefits of prosecuting potentially harmful, abusive, and anticompetitive business conduct facilitated by AI against the costs of capturing, stymieing, and deterring potentially beneficial and innovative business practices—as well as investment in cutting-edge AI technology.

For decades, the primary objective of US antitrust laws has been to protect the competitive process and to benefit consumers—by preserving incentives for businesses to act efficiently, by keeping quality high and prices and costs low, and by utilizing quantitative tools of economic analysis to support enforcement decisions. With certain exceptions where there are no reasonable procompetitive or consumer-benefiting implications, conclusions about whether a business practice is likely to harm or benefit consumers and competition are made on a case-by-case basis. This is known as the *consumer welfare standard* (CWS). It has made antitrust law a flexible, pragmatic tool that has been successfully adapted to emerging technologies by judges. Recently, however, some academics and antitrust enforcers have called for abandoning the CWS in favor of protecting competitors and disfavoring large businesses. They have also called for incorporating extraneous factors to antitrust law, such as labor rights, environmental regulation, and special small-business protections. This would politicize antitrust law while increasing costs and uncertainty for businesses and hindering innovation.

Antitrust laws, including the Clayton, Sherman, and FTC Acts, attempt to stop firms from reducing competition in the marketplace or maintaining monopolies. They single out specific business practices and mergers for possible prohibition or punishment while allowing courts to decide whether the practices or mergers are illegal, depending on the circumstances of each case. Robust economic competition supports productive, innovative markets; it facilitates the introduction of new or improved products while supporting scientific, technological, and creative progress, as businesses compete with each other to best address consumers' wants and needs. In short, vigorous competition delivers better or more cost-effective products. By contrast, ineffective competition means that businesses can maintain their market share by excluding rivals; defective competition laws protect businesses from competition, when the laws should instead maintain incentives for businesses to compete vigorously and serve consumers well.

This primer will explore the likely consequences of recent trends in antitrust enforcement for the development of AI, affecting such factors as attracting and maintaining a user base and accessing data, cloud-computing power, advanced hardware (such as semiconductor chips), skilled talent, and the use of algorithms to facilitate pro- and anticompetitive conduct. In addition, there are the implications of foundation models that are increasingly relied upon by a large number of firms across vast swaths of entire industries as well as future developers of new AI tools. This work will also lay out overarching principles for policymakers, regulators, and judges to keep in mind when navigating the trade-offs of antitrust regulation of AI. The goal is to ensure that a dynamic, competitive, and innovative ecosystem for the development of future AI technologies is preserved.

AI also carries implications for user safety, data privacy, intellectual property (IP) rights, and national security. Some of these concerns intersect with competition and consumer welfare. Others are best targeted and addressed through their own statutes or regulatory frameworks that single out specific harms tied to specific industries and applications.

ARTIFICIAL INTELLIGENCE: KEY CONCEPTS AND COMPONENTS

This section will address key concepts and components of AI technologies. Additionally, access to adequate capital,[4] skilled technical labor,[5] and resource inputs are also critical for AI development and innovation. Understanding these concepts is essential for understanding the antitrust and competition implications of artificial intelligence and how US antitrust enforcers and regulators should best approach AI and AI-adjacent markets. Though regulators, enforcers, and policymakers need not have the same level of understanding as a software professional or technical expert, they should have the "confidence to ask the right questions; the ability to understand engineers' explanations; and, crucially, the capability to question technical experts."[6]

Foundation models. These are large-scale AI software systems that are trained using large data sets to perform a range of downstream tasks,[7] including decisions and predictions.[8] Foundation models have been used to power a range of applications: Image generators like Midjourney can produce near-human-quality artwork in response to prompts,[9] and text generators like OpenAI's ChatGPT can produce detailed and logical responses to text prompts, including research inquiries.[10] As models evolve and improve their capabilities, they can rapidly reach obsolescence, resulting in their replacement by newer models. For instance, as of February 2024, Google's Gemini chatbot is powered by the Gemini Pro model, which replaced the less powerful PaLM-2 model, which (in turn) replaced the less powerful LaMDA model.[11]

The knowledge base of the model and the accuracy of its algorithm (code) are adjusted by feeding it data. *Pre-training* is the phase in which a foundation model's knowledge base is set up through data inputs by the designers.[12] *Fine-tuning* is the phase in which the model is refined for specific uses and applications[13]—for instance, for a software-code writing assistant, or a customer-service chatbot.

Model size. The current market trend is for foundation models to grow larger. For instance, BERT was an early foundation model released in 2018. It had just 354 million trainable parameters (values that are used to compile the model's knowledge base).[14] By contrast, recent models like GPT-3 (which powers ChatGPT), PaLM, and so on have hundreds of billions of trainable parameters.[15] Even popular open-source models that are used by scores of developers today have tens of billions of trainable parameters.[16] The economies of scale afforded by larger models enable better performance and predictive power;[17] however, larger models are also more costly to create and run, necessitating access to more training, more fine-tuning of data,[18] and more computation power.[19] In the future, we could witness a plateauing of size-based model performance, which could work to the advantage of smaller, less costly models that are energy efficient and computing intensive.[20] Applications without heavy performance demands can already run smoothly on smaller models. The existing and foreseeable trend toward increasing model size helps larger, well-resourced model-developer firms;[21] however, there is currently a thriving competitive market for pretrained foundation models consisting of a mix of open-source models (freely available) and closed-source proprietary models that are available to independent application developers under commercial license terms.[22] There is also a thriving market of external computing and database firms whose services are available to those lacking access to computing power or server space of their own.[23] Thus, smaller AI software firms that do not own their own data troves or computing facilities are not barred from entering the market and challenging larger incumbents.

For instance, major foundation-model developers, including Google, Microsoft, and Amazon, own infrastructure that is important for creating and distributing foundation models, including data banks, data warehouses, and cloud servers.[24] In addition to supporting their own foundation-model-related business, they also engage in commercial partnerships and investments that support the development of other models and AI-related businesses. For instance, Microsoft and Google provide cloud-computing services to foundation-model developers like OpenAI[25] and Anthropic, respectively.[26]

Machine learning. *Machine learning* is the process of training an AI foundation model by iteratively refining its inference-making process through feeding it real-time or stored data.[27] With every new data input, the model learns and adjusts its predictions to reach a more accurate or desired outcome.[28] For example, image generators like DALL-E and Midjourney were originally trained with data inputs that included various human artworks,[29] thus refining their ability to imitate or reproduce humanlike art. These inputs can be fed to the model by software engineers in the pretraining or fine-tuning phase, or they can be fed in real time by users during the fine-tuning phase.[30]

The AI triad: software algorithms and code, chips, and data. These are the key components of any AI system.[31] *Algorithms* are a logical sequence of steps that perform a task,[32] and in computers they take the form of software code. These may be proprietary in nature. They are deployed to produce inferences and to engage in machine learning, which in turn refines the algorithm. The production of proper inferences is usually contingent on millions of data points as well as many rounds of training. AI foundation models make use of one or more algorithms.

Data "are the digital raw material used to train models during the machine-learning process as well as the input on which trained models make inferences,"[33] and other finished products. Both the volume and variety of a data set are important when it comes to training AI models to make accurate, reliable, and tailored inferences through machine learning.[34] Real-world diversity and complexity can only be reflected in a diverse and representative set of data. Unique cases and outliers can only be identified and treated appropriately if machine learning has been conducted using a varied data set.[35] For example, an AI model designed to perform facial recognition on a diverse population would perform far worse if it were trained on a high-volume data set of Caucasian faces, or a set confined largely to a single gender, than it would if it were trained on a smaller set of data that was more representative in ethnicity and gender.

The amount and quality of data necessary for training an AI model to make adequate or accurate inferences depends on the application's complexity,[36] the size of the model,[37] and the accuracy requirements of the specific task. For example, research on text-based AI models shows that using high-quality data provides a significant boost to the model's performance relative to average-quality data.[38] In the case of text-based models designed to produce software code, the improvements in the accuracy of the final products are estimated to be as high as 71 percent.[39] Increased demand for data, including proprietary data, has led to the emergence and evolution of data markets. For instance, technology companies and publishers are already making deals for the use of the publishers' proprietary data in the training and fine-tuning of the tech companies' models.[40]

Small-data strategies are used to train models effectively when large volumes of representative data may be scarce or unavailable or when more-extensive data collection would raise privacy concerns.[41] *Transfer learning* is when "a model 'inherits' learned information from previously trained models."[42] *Artificial data* are fake (albeit representative) data that are created synthetically.[43] Such data will often need to be supplemented with human feedback and inputs to prevent degradation of the model's performance.[44] *Bayesian methods* involve providing models with prior contextual information to preemptively overcome learning challenges.[45] *Reinforcement learning* limits the need for data when the outcome sought by the application is known but when the steps to get there are not clear;[46] it involves placing an AI agent in an environment and allowing it to learn by trial and error through repeatedly performing some task, trying to achieve some goal, or maximizing some value.[47] Constant repetition until the goal or objective is met produces reward signals that drive code adjustments; these in turn improve subsequent trials and allow the agent to reach the goal more efficiently.[48] A driverless AI-powered car, for example, can be tasked with maximizing fuel efficiency or minimizing distance traveled between two locations, if these locations are known beforehand.

Data storage is critical because AI models can only function efficiently and effectively, and learn quickly, if the data that they use can easily be collected, stored, and accessed.[49] Data may be stored close to the point of application for quick and easy access or may be stored in centralized data warehouses that consist of hundreds of servers.[50]

Data cleaning involves sifting through messy, disjointed, and usually incomplete data to manually remove information or data points that are irrelevant or outliers and manually filling in gaps in the data through suitable methods and techniques.[51] Data cleaning also entails categorizing and labeling data or data subsets.[52] Cleaning ensures that machine learning is most likely to produce accurate or reliable inferences or desired outcomes that meet specific standards. Decisions about what to remove and how to label data are heavily contingent on the specific application. It is estimated that data cleaning and other forms of data preprocessing occupy 80 percent of engineering time.[53] This underscores the need for a sufficient number of skilled technical workers to ensure competitiveness and innovation in AI.

Microchips (chips) are sets of electronic circuits on a small, flat piece of semiconductor material such as silicon or germanium.[54] Chips store data and provide processing power to run AI algorithms. A chip's speed and computing power come from semiconductor switching devices called *transistors*.[55] The smaller the size and the greater a chip's transistor density, the greater its power and speed.[56] Chip innovation has historically been driven by reducing transistor size and fitting more on each chip.[57] Technological improvements in chip technology have rapidly escalated over the last 40 years, with processing speed increasing by 200 percent approximately every two years—a phenomenon known as "Moore's Law."[58] This has allowed for increased data storage and increasingly complex and innovative AI applications.[59] However, this pace of evolution is unlikely to remain sustainable as chips reach their physical limits.[60] Though chip innovations continue beyond transistor shrinkage and improvements in density, these often increase cybersecurity risks by creating hardware vulnerabilities that are difficult and costly to mitigate.[61]

Cloud computing. This refers to computing resources that are remotely located.[62] Such digital services are usually provided by specialized cloud-computing companies or specialized divisions within larger firms, which control vast volumes of powerful servers.[63] Because in-house procurement of the required computing power is not feasible for many AI developers because of the high cost, cloud-computing services foster competition in AI industries by lowering entry barriers.[64] The UK Competition and Markets Authority reports that as of 2023, most AI foundation-model developers contract with cloud-computing providers for the computational resources necessary to train their models.[65] Decentralized cloud computing allows AI components to operate from different locations, meaning that AI software engineers do not need to own the data they use;[66] they need only receive access from the data owner whose data may be stored on a range of cloud servers in various locations. This can protect the privacy of the users from whom the data may be derived by eliminating the need for their data to be aggregated in a single location that is vulnerable to hackers.

ANTITRUST LAWS AND ENFORCEMENT: AN OVERVIEW

This section on antitrust laws and enforcement provides an overview of three main federal antitrust statutes and the two main antitrust enforcement agencies.[67] Additional state antitrust laws are enforced by state attorneys general or private plaintiffs.

The Sherman Antitrust Act of 1890

The nation's first antitrust statute emerged in response to concerns that trusts (like Standard Oil) and large, industry-dominating companies like US Steel—big companies that were involved in the rapid expansion of the US economy in the late 1800s—could threaten American democracy and harm ordinary citizens through monopolistic practices.[68]

- **Section 1 of the Sherman Act** bans "every contract, combination, or conspiracy in restraint of trade." The Supreme Court has interpreted this provision as outlawing only "unreasonable" restraints of trade, recognizing that some restraints of trade are reasonable or even a pragmatic necessity for certain business practices—forming a partnership, for example. However, some restraints of trade are considered so deleterious toward competition that they are regarded as illegal per se and have no legal justification, such as agreeing with one's competitors to fix prices or to rig bids for procurement. Other restraints of trade are evaluated for their anticompetitive harm by courts through a case-by-case "rule of reason" that assesses whether a practice's procompetitive benefits outweigh its anticompetitive harms. In recent decades, courts have increasingly embraced the rule of reason for business practices previously deemed illegal per se, because of a better economic understanding of those practices' potential procompetitive effects. Notably, the Supreme Court has criticized "[l]egal presumptions that rest on formalistic distinctions rather than actual market realities."[69] Where the circumstances of the trade restraint are complex, the court is highly unlikely to apply a rule of per se illegality.[70]
- **Section 2 of the Sherman Act** outlaws "monopolization, attempted monopolization, or conspiracy or combination to monopolize." Importantly, this section doesn't penalize the acquisition of monopoly power in a market through "growth or development as a consequence of a superior product, business acumen, or historic accident."[71] Rather, it penalizes certain exclusionary conduct in business that increases or safeguards monopoly power

and is not tied to competition "on merit." For instance, Microsoft was punished in the 2001 Supreme Court case of *United States v. Microsoft*,[72] not for acquiring monopoly power in the PC operating-system market, but for certain business practices that prevented its competitors from legitimately challenging its monopoly. Section 2 claims are generally evaluated under a rule of reason.[73]

- **Criminal violations of the Sherman Act** are prosecuted by the Antitrust Division of the Department of Justice and can attract fines of up to $100 million for corporations or $1 million for individuals, with potential prison terms of up to 10 years. Federal law allows for a maximum fine of up to twice what the conspirators gained from the illegal conduct, or twice what the victim lost because of the crime. These are typically reserved for hardcore illegal, clear, and intentional violations of Section 1. Section 2 violations and other violations of Section 1 are typically resolved through civil penalties or, when other remedies are not sufficient, through imposing structural changes on companies to break up monopolies, as when AT&T agreed to break itself up into multiple companies as part of a 1982 settlement with the DOJ.[74] Sherman Act violations also violate Section 5 of the Federal Trade Commission Act, but the FTC may only obtain injunctive relief or orders to "cease and desist" under its statute.

The Clayton Antitrust Act of 1914

The FTC, along with the DOJ, has authority to enforce the Clayton Antitrust Act of 1914.[75] Mergers and acquisitions whose effect "may be substantially to lessen competition, or to tend to create a monopoly" are banned by Section 7 of the Clayton Act. Amendments to the Act under the 1976 Hart-Scott-Rodino reforms mandate that companies intending to undertake mergers and acquisitions beyond a certain size must provide a premerger notification to the government so the transaction can be reviewed for potential Section 7 violations.[76] The FTC may seek an injunction to block proposed mergers that it deems illegal, pending a full examination of the deal before an administrative law judge. This preserves the market's competitive status quo until the dispute is resolved. Another Clayton Act provision, incorporated under the Robinson-Patman Act, bans certain exclusive discounts and services when suppliers deal with merchants.[77] The Clayton Act also allows private parties to bring a lawsuit for triple damages when they have suffered harm due to violations of either the Clayton Act or the Sherman Act, or to get court orders prohibiting the anticompetitive practice in the future.

The Federal Trade Commission Act of 1914

The Federal Trade Commission Act of 1914 prohibits "unfair methods of competition,"[78] which courts have deemed to include all violations of the Sherman Act[79] and several violations of the Clayton Act.[80] In addition, this provision may also reach practices, such as invitations to collude,[81] that harm competition but do not fit squarely into conduct categories covered by the

Sherman and Clayton Acts.[82] The Federal Trade Commission Act also created the FTC, an expert administrative agency tasked with prosecuting violations of its provisions, as well as those of the Sherman Act and Clayton Antitrust Act. Private parties and the DOJ cannot sue for violations of this statute.

Antitrust Enforcement Agencies: DOJ and FTC

Criminal and civil antitrust law violations are investigated and prosecuted by the DOJ and FTC. However, only the DOJ can bring criminal lawsuits and seek criminal penalties in federal court. Each agency specializes or has subject matter expertise in different industries and industry subsets. Given the FTC's dual focus on consumer protection and antitrust matters, it tends to focus resources on economic sectors that involve high consumer spending. These include healthcare, pharmaceuticals, professional services, food, energy, and high-tech industries (e.g., computing and internet services). Conversely, the DOJ has sole antitrust jurisdiction in certain industries, including telecommunications, banking, railroads, and airlines. AI-related antitrust issues notably cut across all these industries and are encountered by both agencies.

Agency investigations are initiated after receiving premerger notification filings and tips or complaints from informants, businesses, or consumers. They may also be prompted by congressional inquiries or academic journal articles. If an antitrust law violation is identified, then the agencies may first seek a voluntary compliance (or consent) order that allows the offender to avoid admitting guilt if it agrees to cease the offending practice or, in the case of mergers, if the entity agrees to undertake structural changes to the business to avoid a merger's potential anticompetitive implications. Under the DOJ's leniency program, parties that inform on serious anticompetitive conduct, such as cartel behavior or bid rigging, may be able to avoid criminal trials against their own conduct by entering into court-administered settlements with the agency.

The FTC maintains its own internal administrative-complaints process. An administrative complaint triggers a formal proceeding before an administrative law judge that is somewhat similar to a federal court trial: Evidence and testimony are presented, and witnesses are examined and cross-examined. A cease-and-desist order may be issued for law violations. The administrative law judge's decision may be appealed to the FTC, and final decisions of the FTC may be appealed to the US Court of Appeals and ultimately, to the US Supreme Court. The FTC may seek an injunction or civil penalties if a company violates a final order from the FTC. Since it cannot seek criminal penalties, the FTC may refer evidence of criminal violations to the DOJ. If the DOJ cannot reach a consent order with the offending party, then it can sue the party in federal court to obtain an injunction against the offending conduct or to obtain criminal penalties for clear, intentional violations of Section 1 of the Sherman Act. The DOJ and FTC also cooperate with many of the 130-plus national competition law authorities worldwide to investigate transnational firm conduct and promote best practices in global antitrust enforcement.

Besides the DOJ and FTC, state attorneys general may also bring federal antitrust suits on behalf of in-state residents or businesses, or on their own behalf. State antitrust laws may go beyond federal laws, imposing extended liability theories and prohibiting a wider range of conduct. State attorneys general may also cooperate with federal agencies in investigating mergers or may join the federal agencies as parties to lawsuits. Private parties, including aggrieved businesses and individuals, can also seek civil damages for (or injunctions against) Clayton Act, Sherman Act, or state antitrust law violations affecting them.

THE CONSUMER WELFARE STANDARD

This section provides an overview of the consumer welfare standard and recent calls for abandoning it.[83] Since 1979, the Supreme Court has stated that consumer welfare enhancement is the ultimate goal of antitrust law.[84] The CWS recognizes that competing vigorously in business "on the merits" benefits consumers through outcomes such as lower prices, greater product variety, better or more efficient services, and greater innovation. This benefit holds true even if competitors are harmed in the process. Courts recognize that seeking a monopoly position is itself a powerful incentive for competing vigorously by delivering goods and services that consumers demand and that such an approach may not necessarily leave consumers worse off.[85] The CWS was grounded in research work by economists from the Chicago and Harvard schools of antitrust. Harvard and Chicago scholars also recognized that an overly aggressive approach to antitrust enforcement, including the punishing of conduct or blocking of mergers based on purely speculative harm to consumers and competition, would raise substantial administrative costs and error costs that could undermine beneficial, procompetitive behavior and deals. Such an approach thus would deter, rather than uphold, competition and consumer welfare.[86]

Leading researchers define the CWS as behavior that tends to maximize some combination of the quantity and quality of output and innovation, within the context of sustainable competition.[87] Thus, unsustainably below-cost predatory pricing—to eliminate a rival from a market with the reasonable possibility of recouping one's investment by raising prices later—remains punishable by law, as it would harm both competitors and the competitive process itself. However, aggressive competition through lower prices is recognized as giving consumers exactly what they want, while allowing businesses to out-compete their rivals; there is nothing in this healthy process that excludes others from successfully competing.[88] The CWS has driven key court decisions that have gradually abolished prohibitions on potentially procompetitive business practices, such as bundling products[89] and negotiating exclusive discounts from suppliers.[90] This gives businesses more leeway to compete vigorously and expand scale and operations regardless of whether this put them in a position to capture large shares of the market and become a "monopolist." However, some manifestly anticompetitive business conduct still remains illegal, including cartel behavior, price fixing, and bid rigging. These practices have no reasonable procompetitive or consumer-benefiting implications.

A parallel, related development to the CWS has been a shift from superficial focus on market structure[91] toward sophisticated analysis of mergers and other business conduct, using the tools of economics to identify and build a case for theories of harm.[92] Novel evidence-based theories of harm are investigated and prosecuted on a case-by-case basis in cognizance of how rapidly evolving industries and markets can bring about new competitive dynamics. These theories of harm are weighed against any potential procompetitive benefits. Courts consider not only the ability but also the incentive of a firm to raise prices and restrict output in a particular market,[93] such as after a merger. For instance, holding a patent over a production input is not considered sufficient evidence that the holder has monopoly power sufficient to "foreclose" rivals if competitors are capable of securing or are likely to secure substitute IP-protected or unprotected inputs in the relevant market.[94] This applies to some markets and industries rather than others. For instance, patented pharmaceutical drugs often do not have substitutes that patients can use or that rivals can provide without violating the patent.

The Neo-Brandeisian Resurgence: Calls for Abandoning Consumer Welfare

Since 2016, there has been a resurgence in calls for abandonment of the CWS and a more interventionist approach to antitrust matters that is focused on market structure and political goals. Proponents of this movement label themselves *neo-Brandeisians*, a reference to early-20th-century Supreme Court justice Louis Brandeis.[95] They take a negative view of businesses growing beyond a certain size and decry an increase in concentration within many sectors of the economy;[96] they blame this phenomenon for reducing rather than increasing competition.[97] Instead of focusing on consumer welfare as a barometer of economic competition, they call instead for antitrust law to focus on company size, workers' rights, protectionism for small business, economic "fairness," and impacts on democracy.[98] They also call for harsher, more aggressive antitrust remedies, including breakup of companies, increased penalties for anticompetitive conduct, greater public regulation of firms and markets, and governmental control or even nationalization of many enterprises.[99] Digital platforms including Meta, Google, and Amazon have become key targets of the neo-Brandeisians.[100]

These theories are not supported by economics or the law. Moreover, their proponents propose an approach to antitrust enforcement that violates the rule of law. Flaws of the Neo-Brandeisian approach include the following:

- **It is premised on unfounded claims and flawed research.** Research advanced by neo-Brandeisians to support an economy-wide increase in market concentration[101] rely on overbroad market definitions or generalizations about entire industries that do not account for the competitive dynamics of specific markets or consistent economy-wide trends across markets.[102] Higher concentration and higher markups could be the result of anticompetitive or exclusionary conduct; however, they could also be the outcome of market share acquired through superior products or more efficient production processes. Larger companies are often able to take advantage of economies of scale (lower costs per unit) and cross-subsidies from participation in two sides of the market.[103]

- **It is counterproductive for upholding competition as well as benefiting consumers and innovation.** Neo-Brandeisian proposals and the aggressive antitrust enforcement approach that they champion are likely to leave consumers worse off because of "false positives" for alleged anticompetitive conduct. In markets where competition has declined, more aggressive government regulation and intervention is often a driving cause or a counterproductive remedy. "As historic regulatory reform across American industries has shown, cutting government-imposed barriers to innovation leads to increased competition, strong economic growth, and a revitalized private sector."[104] Even if aggressive antitrust enforcement against potentially procompetitive business conduct captures some anticompetitive conduct that might otherwise take longer to attract regulatory attention, this approach leads to firms being deterred from pursuing business strategies that benefit consumers, harming vigorous competition rather than upholding it. Businesses will be forced to expend more resources in dealing with regulators, courts, and enforcement agencies, rather than on improving products, services, or business processes. Similarly, breaking up companies would reduce scale economies, and is thus likely to harm consumers and increase the costs they face. In innovation-intensive industries like AI and other tech sectors, neo-Brandeisian antitrust enforcement can thus curtail innovation by deterring the practices that foster it. For example, preventing digital platforms from achieving a certain size and scale could preclude them from taking advantage of network effects of a large database of users for training cutting-edge models; it could also prevent them from deploying novel technologies at scale and enabling their rapid adoption. Thus, a neo-Brandeisian enforcement policy could drive some platform-specific innovation from the United States to other countries that create a more favorable environment for innovators—and investors in innovations.
- **It conflates economic competition with unrelated policy objectives, thereby undermining the rule of law.** The neo-Brandeisian proposal for including multiple, disparate factors in developing antitrust policy and enforcement approaches—such as labor, the amorphous concept of "fairness," and environmental interests—creates substantial difficulties in balancing competing objectives that often cannot be assessed or weighed against each other by empirical means. Thus, more arbitrariness and less transparency and predictability would be inserted into antitrust enforcement and policy decisions, thereby creating an environment unfavorable to business innovation where the rule of law is undermined. Factors outside consumer welfare are best addressed through separate policies and legislation that is not conflated with the goals and economic-analysis underpinnings of antitrust law (for instance, through labor law or environmental regulations).

Horizontal Mergers

Horizontal mergers occur when a firm acquires a competitor at the same level of the supply chain, thus reducing the number of competitors in the relevant market. Because there are fewer competitors, the merged firm could theoretically leave consumers worse off while maintaining or increasing its profitability by reducing output or product quality relative to price.[105] The ability to do so constitutes an exercise of market power. The potential anticompetitive effects of a merger can be unilateral or coordinated. *Unilateral effects* emerge from the postmerger firm's conduct in isolation, such as raising prices and reducing output without regard to the actions of remaining competitors.[106] *Coordinated effects* refer to coordinated action by the merged firm and its remaining competitors, such as tacit collusion to coordinate prices. These actions become theoretically easier post-merger.[107] The potential unilateral and coordinated effects of a merger constitute *theories of harm* for plaintiffs trying to block mergers.

Conversely, horizontal mergers can benefit consumers and increase innovation through reallocating underperforming assets to more productive uses;[108] creating a more efficient entity capable of using its larger scale, collective expertise, and pooled resources to reduce prices; increasing product quality and output; deploying products in a wider range of markets and contexts; and investing more in innovation, research, and development.[109] Such mergers increase rather than reduce competition by creating an entity that competes more effectively both overseas and domestically. These efficiency gains and benefits can manifest regardless of whether or not the merged entity operates in a concentrated market, provided that existing competitors or new firms can enter the market and erode the market share and profit margins of the incumbent firm by vying for its customers.[110]

Thus, a key issue in antitrust policy is the trade-off between potential market power effects and potential efficiency effects after a merger. Potential efficiency gains can often counteract market power effects, thereby making a merger's net effect on welfare ambiguous. It is important to consider both the incentives and the ability that the postmerger entity will have to either compete vigorously and benefit consumers, or harm consumers by increasing price relative to output and lowering product quality and innovation in the relevant market.[111]

The structural presumption. In 1964, the Supreme Court adopted a view championed by mainstream economic thinking at the time that any horizontal merger that creates an entity with a market share of over 30 percent of the relevant market is presumptively a threat to competition and therefore illegal.[112] This is known as the *structural presumption* in horizontal merger analysis. A plaintiff challenging a merger, typically one of the competition agencies, can bolster this prima facie case against a merger with evidence that anticompetitive unilateral or coordinated effects are likely to follow.[113] Defendants appealing an attempt to block the merger then bear the onus of rebutting this presumption by showing evidence that this is not the case for their proposed merger[114] and that the merger will thus not "substantially reduce competition."[115]

Since the 1960s, improvements in economic understanding have led most economists to question and criticize the presumption that a merger is anticompetitive and likely to harm consumers and competition if it establishes control over a certain share of the market.[116] The focus on market concentration to discern probable anticompetitive effects has been criticized as "clumsy and inaccurate in industries with differentiated products where the theory of harm is related to unilateral (rather than coordinated) effects."[117] Varying industry and market-specific conditions mean that there is no systematic causal relationship between market concentration and performance measures, such as prices and margins.[118] Even in highly concentrated markets, a significant number of mergers can result in lower prices, thus benefiting consumers.[119] The superior efficiency of larger firms in markets characterized by innovation and differentiated products can also lead to their becoming concentrated without reducing consumer welfare.[120] This holds especially true for high-tech innovation-intensive industries like AI, as economies of scale possessed by larger firms are essential for delivering cost-effective data compilation and model training and cloud computing. Smaller companies and developers benefit too, either by being acquired and seeing their innovations deployed at scale by larger companies, or by contracting with larger firms for services that would not be cost-effective if conducted in-house,[121] or by licensing proprietary technology such as advanced, closed AI foundation models.[122] Consequently, blocking high-tech acquisitions purely based on market concentration can significantly harm innovation and thus consumer welfare by precluding these procompetitive outcomes.

The structural presumption is useful to competition agencies, as it makes it easier for agencies to secure victories in blocking mergers, and it provides some commercial certainty to merging parties that would have a postmerger market share below the threshold that indicates a significant likelihood of challenge.[123] However, the structural presumption also risks deterring procompetitive mergers by raising the costs of undertaking one. Accordingly, the FTC and DOJ have, until recently, deemphasized a focus on mere concentration figures in order to reduce the risk of wasting agency resources in challenging mergers that are likely to be procompetitive. Under their 2010 merger guidelines, which signaled to commercial parties what mergers the agencies are likely or unlikely to challenge, the agencies highlighted a holistic analysis of the relevant market that accounts for industry and market-specific factors as well as an upward pricing-pressure metric that estimated the value of diverted sales to the merged entity's competitors should it raise prices.[124] Conversely, the FTC and DOJ in their 2023 guidelines signaled a return to challenging mergers primarily on the basis of the structural presumption.[125] Litigating against an FTC or DOJ attempt to block a merger (or appealing an injunction secured against a merger) is a costly, multiyear process that often forces parties to abandon mergers even when the mergers could have survived a court challenge.[126] These costs could thus increase drastically under current FTC and DOJ leadership, which has shown a greater tendency to prosecute deals even when their prospects of blocking the merger in court are low.[127] There is already evidence that this approach has had a chilling effect on dealmaking in a range of markets, likely deterring or blocking a range of pro-innovation, pro-competitive deals.[128]

Killer acquisitions. *Killer acquisitions* refers to a theory of harm typically involving a larger company acquiring a smaller, innovative competitor with the goal of deliberately killing off a potential (or actual) competing product or innovation, thereby leaving consumers worse off than if the merger had not taken place.[129] It is largely based on a 2019 article by Cunningham et al. that studied the pharmaceutical sector.[130] The authors found that killer acquisitions were more likely when the acquiring firm derives more potential profits from shutting down a new project (i.e., by the firm being acquired) than it would from bringing the new project to market.[131] They claimed that that the killing of acquired-firm projects was particularly likely when there was an overlap between the product portfolios of the acquiring firm and the acquired firm and when the acquiring firm had substantial market power stemming from patents with long remaining lives. According to the authors, 5.3 to 7.4 percent of acquisitions in the pharmaceutical sector are killer acquisitions.[132] The study has been criticized for exclusively focusing on one industry (thereby ignoring factors specific to others, such as the tech sector)[133] and for failing to account for the unique dynamics of the pharma industry, thereby falsely branding acquisitions that did not cause consumer harm as killer acquisitions.[134]

In the tech sector, the ability to produce and deploy products at a massive scale, rather than just possessing the resources necessary to invest in research and development, is a key advantage possessed by larger firms relative to smaller competitors. A 2020 survey of acquisitions by Google, Amazon, Facebook, and Microsoft canvassed the 175 firms that had been acquired by these tech giants between 2015 and 2017 and found that most of these transactions resulted in the acquired firm's technology, talent, IP, and functionality being integrated into the acquiring firm's ecosystem.[135] This indicates that acquiring firms were using acquisition to supplement and to substitute for their in-house research and development.[136] Only a single acquisition out of the 175 canvassed was identified as a possible killer acquisition.[137] These differing factors attest to the need to closely examine the surrounding factors in each individual merger before assuming the applicability of novel theories of harm that are likely to manifest in alternative contexts. A false-positive blocking of a merger on the basis of the killer-acquisition theory could cause immense harm to consumer welfare and innovation by entirely preventing or delaying the deployment and development of new technologies using the scale necessary.

Vertical Mergers

Vertical integration is when a firm acquires an asset or merges with another firm to enter an upstream or downstream market.[138] Examples of vertical integration include a newspaper's acquisition of a printing press, a retailer's acquisition of a wholesaler and a logistics company, or a video-game console company's acquisition of a game developer.

Unlike horizontal mergers, it has long been recognized that vertical mergers virtually never pose a threat to competition when undertaken in competitive markets and that they typically benefit consumers by creating procompetitive efficiencies.[139] Firms tend to vertically integrate to reduce the cost of repeatedly coordinating and contracting with each other on an open market.[140] Since the acquiring firm and acquirer are not direct competitors, the integrated entity would have greater incentive to pass on savings from these reduced costs, as well as savings from expanding their scale of operations through leveraging the merged entity's greater resources. The vertical merger of two firms also creates incentives for price reductions that are potentially passed on to consumers through eliminating "double marginalization," or the levying of profit margins at two stages of the supply chain.[141] In addition, firms often vertically merge or integrate into different levels on the supply chain to take advantage of a unique position in one market to improve offerings in another.[142] For instance, it would be logical for a large digital market platform or retailer that ships a large volume of products to acquire its own logistics and warehousing division, because its shipping volumes would allow it to lower costs by shipping in bulk. These features set vertical mergers apart from horizontal ones.

This is why courts[143] and agencies (including the FTC and DOJ)[144] have historically taken a less skeptical view of the notion that efficiencies created by vertical integration will be passed on to consumers. Between 1994 and 2016, the FTC and DOJ contested only 52 vertical mergers, and some of these also entailed horizontal overlaps.[145] Typically, those cases involved significantly greater focus on the potential anticompetitive concerns raised by horizontal aspects of the transaction.[146]

There are situations in which a vertical merger or vertical integration could still raise anticompetitive concerns. For example, imagine a large firm with few rivals in an industry in which a key production asset at another level of the market is controlled by a single firm. The large firm could acquire that single firm, gaining exclusive control over its input and plausibly harming competition by raising the prices it charges to its rivals for that input.[147] The likelihood of this depends, however, on market-specific conditions supporting the merged firm's ability and incentive to act. Even if market conditions indicated that this theory of competitive harm was likely, the possibility of harm could be mitigated or eliminated by requiring the merged entity to sign long-term contracts to deal with its rivals on commercial (fair and reasonable) terms. Such a requirement could be made a condition of the merger.

In the AI context, certain inputs may exist in concentrated near-monopoly markets in which a downstream company, such as a foundation-model developer or finished hardware or computing company, could theoretically raise its rivals' costs, harming competitors and consumers, by acquiring the upstream monopolist or oligopolist firm. For example, the ultraviolet lithography machine used to manufacture leading chips used by AI foundation models is patented by a single manufacturer, the Dutch firm ASML Holdings.[148]

Conversely, many examples of vertical integration are crucial for innovating and deploying AI foundation models. For example, cloud-computing firms can take advantage of economies of scale from their server capacity to subsidize computing costs for their own foundation models; they can then deploy these models on a greater scale and with greater access to their user base. Inputs from that user base can be used to fine-tune model algorithms by offering them to application developers who purchase cloud services. Google, Amazon, and Microsoft all provide cloud services to a range of application developers and foundation-model developers while developing their own models and application programming interfaces (APIs) in house. Similarly, social media companies like Facebook/Meta and search engines like Google can take advantage of their large user base of consumer data to refine and train better-quality foundation models in house; part of this process may include acquiring developers who hold promising technology.

Algorithms and Collusion

AI algorithms bring immense benefits to both firms and consumers by making the former more efficient and capable of bettering their services and tailoring product recommendations to individual consumer preferences.[149] Similarly, price-setting or recommendation algorithms help firms respond efficiently to real-time market conditions and could increase "accuracy in detecting changes in price, greater speed in pricing response"; they could also reduce "irrationality in discount rates."[150] However, these algorithms can also lead to anticompetitive outcomes by reducing the market's risk-related incentives to provide discounts at all[151] or by facilitating express or tacit collusion between firms to raise prices and restrict output.

Price-matching algorithms that swiftly allow sellers to match discounts offered by their rivals could reduce the incentive for sellers to offer discounts in the first place.[152] Theoretically, this could lead to firms' collectively adopting a monopoly price as a rational response to the prevalence of the price-matching algorithm among competitors in order to prevent a "race to the bottom" that erodes profits and forces unsustainably low prices.[153] The incentive to do this is heightened in markets where sellers face high fixed costs of entering the market and low marginal costs of production thereafter. Such sellers must set prices at levels allowing for a markup above marginal cost to recoup their fixed costs in the long term.[154] Some researchers argue that these features are especially prevalent in e-commerce, or online shopping,[155] especially across large platforms like Amazon or eBay where customers face low costs in searching for and switching between substitute products—a practice that increases the incentive to closely and rapidly monitor rivals' prices.[156] However, these fears remain largely speculative. And any strategy of raising prices with the expectation that competitors will consistently do the same carries significant long-term incentives for individual competitors to cheat by halting price hikes to draw market share away from other market participants. Undercutting rivals on price is a procompetitive, proconsumer business practice that is only sustainable and viable in the long term if it does not result in the prevalence of unsustainably low prices. Algorithms that prevent unsustainably low prices can thus be part of a procompetitive and rational business objective.[157] These algorithms can also avert potential antitrust violations by reducing the risk that a strategy of undercutting rivals on price will give rise to predatory pricing complaints.

If human sellers explicitly agree to align their algorithms to set prices, prosecuting them for collusion is straightforward once those facts are established.[158] The US Supreme Court has long held that it is illegal for sellers to agree to fix prices[159] or to jointly raise their prices above procompetitive levels.[160] This principle stands even if sellers conspire to do so by using the same algorithm[161] (or algorithms aligned with each other).[162] The FTC has also reached settlements with firms that have sent "invitations to collude" to their competitors, such as an email proposing to collectively raise prices; it does so under its authority to prosecute unfair methods of competition pursuant to the FTC Act, Section 5.[163] As yet, there is no legal precedent confirming that the FTC has the authority to prosecute invitations to enter into collusive conspiracies as an unfair competition method.[164] However, the FTC's strategy remains a viable option for deterring or punishing attempts at anticompetitive price fixing, and this approach spares the FTC from having to show any likely anticompetitive harm. In exceptional circumstances, soliciting an anticompetitive agreement can also constitute an attempt to monopolize, which contravenes Section 2 of the Sherman Act.[165] Solicitation of such anticompetitive agreements has also been successfully prosecuted as criminal wire fraud outside of antitrust law.[166]

By contrast, *tacit collusion*, or price-fixing by firms without explicit agreement, invitation, or solicitation, is harder to punish and prosecute, whether aided by algorithms or not. The US Supreme Court defines "tacit collusion, sometimes called oligopolistic price coordination or conscious parallelism" as "the process, *not in itself unlawful*, by which firms in a concentrated market might in effect share monopoly power. Through tacit collusion, firms set their prices at a profit-maximizing, supra-competitive level by recognizing their shared economic interests and their interdependence with respect to price and output decisions [emphasis added]."[167] Mirroring or being influenced by the prices of competitors when setting one's own prices is often a rational response to business conditions that is fully consistent with a competitive market. Thus, pricing explained by such a rational response does not, in and of itself, violate the antitrust laws.[168] High markups—including those achieved by monitoring competitor prices—are necessary in many markets for recouping high fixed costs; this is especially true in innovation-driven markets with differentiated products, like tech- and AI-driven industries. Further, such markups may fund future proconsumer innovations through firms' investment in research and development.[169] This makes it undesirable to punish or deter firms for merely raising prices in response to rivals' product prices. Crafting a judicial remedy against mere conscious parallelism on prices may also be impossible, even when it results in anticompetitive outcomes, as it would amount to telling firms to set prices without regard to their competitors' own prices or business strategy.[170]

Tacit collusion convictions thus require sufficient evidence to infer an agreement between the parties to coordinate prices.[171] In practice, this requires evidence of parallel pricing between competitors combined with "plus factors" indicating an intent to collude.[172] Although computer programs and machines lack consciousness and are thus incapable of possessing intent, their workings and design may be studied to ascertain the intended objectives of their creators and users.[173] The decision to adopt the prices recommended by an algorithm, or to automate price-setting based on an algorithm, are intentionally made by humans, who may be criminally liable if their intent in adopting the algorithm or its output can be ascertained.

However, if firms utilize price-setting algorithms that rapidly process mass-pricing data on the market using artificial intelligence, tacit collusion can become more efficient, less costly, more sophisticated, and harder to detect.[174] The decision of firms to adopt a pricing or price-matching algorithm is typically not within the public domain, although it can be inferred through analyzing market and market-participant pricing behavior[175] and can be revealed through the discovery process in litigation once a complaint is filed. AI could make this conduct even harder for enforcers to punish by enabling firms to mirror each other's pricing without even utilizing the same algorithm or algorithms that interact with one another. This would eliminate the need for any kind of agreement. As Davis and Reddy note, "[E]ach machine learning algorithm can be coded to make decisions based on its predictions of the best responses of other parties in the market, and engage in a form of follow-the-leader pricing. This could lead to parallel conduct without prior agreement, which could be facilitated automatically."[176] Predictive AI can thus make tacit price collusion a viable business strategy even in markets with many firms—markets where collusion may not have been viable previously because of the difficulty of monitoring and coordinating prices without direct communication.[177]

Conversely, AI and algorithmic technology's features could also make tacit collusion easier to detect or prosecute. With human actors engaging in collusion, it is sometimes impossible to precisely determine intent without reading minds—thereby making criminal convictions difficult without sufficient circumstantial evidence of an anticompetitive agreement. This often makes it impossible to ascertain whether a business mirrored its competitor's prices as part of a common understanding to avoid competition or merely adjusted prices to ideal competitive levels that match current demand. AI technology, however, is capable of keeping a record of what decisions it made and of the underlying calculations, inputs, and steps it took to reach those decisions.[178] This information could help enforcers if sellers kept records of what their AI algorithms have done. They might do so voluntarily, or the law might incentivize them to do so—for example, by creating an adverse inference of a tacit anticompetitive scheme or agreement if they did not.[179] It could thus be used to unearth evidence about intent and collusive agreement, either in the context of prosecuting explicit collusion or as part of the "plus factors" that are used to infer an anticompetitive agreement where there is tacit collusion.

Monopolization

Monopolization occurs when a dominant firm gains an advantage over its competitors through exclusionary tactics that harm competition rather than benefiting consumers.[180] Examples of exclusionary conduct may, for example, include predatory pricing to drive a rival out of business (before hiking one's own prices) and entering into contracts with third parties that make no business sense other than imposing harm on a rival. In order to succeed in a monopolization suit, a plaintiff must establish that the defendant firm has substantial and durable market power and that it engaged in exclusionary conduct.[181] Because antitrust laws are concerned with harm to consumers and competition, and not harm to competitors, allegedly exclusionary conduct that has procompetitive effects, such as increasing production efficiency, will not generally be penalized. There are three main types of monopolization cases that could impact artificial intelligence.

Predatory pricing. *Predatory pricing* entails selling products at unsustainably low levels with the goal of driving rivals out of business to preserve monopoly power and raise prices in the future. Under US law, plaintiffs must show that the alleged predator not only set its prices below "an appropriate measure" of costs in the short term, but that it also had a "reasonable prospect" or "dangerous probability" of recovering the losses incurred during the below-cost period once it raised prices.[182] Plaintiffs may show that recoupment of costs actually occurred after the fact or that there is sufficient likelihood that costs will be recovered once the strategy is undertaken.[183] The Supreme Court noted that predatory pricing is usually unlikely to be a successful long-term business strategy[184] and that a business intending a predatory-pricing strategy benefits consumers through lower prices without reducing or harming competition when the strategy fails and the business cannot recoup costs.[185] Given the evidentiary burden involved, it is very difficult for plaintiffs to succeed in price-predation claims today.

Refusal to deal. Although a firm is generally free to unilaterally refuse to do business with any other firm,[186] *refusal to deal* constitutes illegal anticompetitive conduct if it serves the purpose of creating or maintaining a monopoly[187]—that is, when a dominant firm's refusal to deal excludes rivals from competing effectively.[188] Refusing to deal, or dealing in discriminatory terms with competitors in licensing or selling a technology or input that is deemed an "essential facility" or "bottleneck input," could theoretically "raise rivals' costs," thereby stymieing competition and causing higher prices to be passed on to consumers.[189] However, declaring a technology to be an essential facility and thus mandating that it be shared with other firms would drastically reduce the commercial incentive to invest in developing such technologies in the first place,[190] thereby undermining future innovation. It also ignores any potential for competitor technologies to emerge in the future, given technological innovation's unpredictable nature.[191] Administering a "duty to deal," including setting its terms and determining what a fair price or other terms might be for such involuntary dealings, is also outside the expertise and administrative capacity of the courts.[192] It is thus exceedingly difficult for refusal-to-deal claims to succeed under US antitrust law.[193]

In the AI sector, there is currently a thriving market for both open-source foundation models and for closed-source models that can be licensed under commercial terms.[194] There is also a thriving market for competing chip designs, with market leaders like the United States' NVIDIA likely to face competition from in-house designs from Amazon, Microsoft, and other firms.[195] Although semiconductor chips are manufactured by many companies across a range of countries, predominantly in Asia,[196] manufacturing facilities for cutting-edge chips remain a relatively concentrated market. The most advanced two-nanometer (nm) chip designs are expected to be produced by Taiwan's TSMC and the United States' Intel in 2024[197] and by South Korea's Samsung in 2025.[198] Technological advances and a combination of public and private investment are likely to see the continued expansion of the manufacturing of these inputs.[199] These features, combined with the evidently rapid evolution of the industry and the technology supplying it, make it unlikely that any particular chip will be deemed an "essential facility," even though a shortage of chips across the market remains a pressing issue for AI innovation, deployment, and global supply chains.[200] Netherlands-based firm ASML Holdings currently remains the only producer of cutting-edge UV lithography machines necessary for AI chip manufacturing.[201] However, there is no indication that this firm is dealing with customers requiring AI chips on illegal anticompetitive discriminatory terms.

Tying and bundling. When a seller that holds monopoly power in the market for a product makes access to it conditional on purchasing another product from that seller, other sellers of that second product may be excluded from competing since their would-be customers are compelled to buy from the seller of the first product.[202] This is a tying arrangement. *Bundling* is a related term, used interchangeably under US antitrust law,[203] referring to the sale of two different products together.[204] *Mixed bundling* occurs if the components are also sold separately, with a discount for purchasing them as a bundle.[205] In most cases, courts will not deem a tying arrangement to be illegal per se, as many tying arrangements are "fully consistent with a free, competitive market"[206] and have procompetitive justifications that benefit consumers. The anticompetitive implications of a tying arrangement can only be ascertained by carefully examining the specific market and industry,[207] and "most tie-ins benefit competition, *even when* the defendant has tying product power [emphasis added]."[208]

For a tying arrangement to be deemed illegal per se, four elements must be satisfied. There must be two separate products involved; the defendant must give its customers no choice but to take the tied product in order to receive the tying product (coercion); a substantial volume of interstate commerce must be affected by this arrangement; and the defendant must have *market power* in the market for the tying product.[209] Market power exists when "the seller has the power, within the market for the tying product, to raise prices or to require purchasers to accept burdensome terms that could not be exacted in a completely competitive market."[210] Mere evidence of price discrimination, or the ability of the seller to sell the tying product at different prices to different consumer segments, does not confirm market power.[211] Some lower courts have also required the plaintiff to show evidence of anticompetitive effects from the tying arrangement.[212] Others are willing to consider business justifications for a tie even if the above elements are satisfied.[213] A defendant's mere possession of a patent covering the tying product does not necessarily confer market power upon the patent holder—plaintiff must prove that the defendant has market power in the tying product.[214] This is because the vast majority of patent-protected products are not economically valuable or commercially viable in the first place,[215] and even those that are commercially viable usually face competition from other noninfringing substitutes.[216]

In the case of "platform software," such as operating systems, courts have applied the rule-of-reason standard to tying and bundling arrangements.[217] Since the utility of platform software (such as a computer or smartphone operating system) is providing a range of different applications and services in one place, it would be inappropriate to assume that the platform and each software component are separate products tied together, rather than a single offering that benefits consumers through convenience, a better user experience, and a reduction in time and resource expenditure relative to independently sourcing or distributing different services and applications.[218] Integrating new functionalities into existing software is an in-demand and sought-after innovation for consumers, as consumers often buy into an entire "ecosystem" of services and applications rather than individual products.[219] Even when the two tied items are considered separate products, technologically and physically integrating them could improve the value of one or both individual products to users as well as to the producer of the complementary product.[220] It is thus appropriate for plaintiffs in such cases to have the opportunity to forward evidence of procompetitive efficiencies that could justify the arrangement.

AI foundation models arguably serve an analogous function to platform software, with individual applications serving as complements and providing more benefits to consumers when the two are integrated in purchases. Similarly, cloud-computing services may be deemed as analogous to platform software. Individual applications or services offered as part of the cloud-computing service package constitute pro-innovation integrations that add value for consumers and thus increase rather than reduce competition. Whether these efficiency justifications are applicable and whether they outweigh the anticompetitive harms of the individual tying arrangement must be judged on a case-by-case basis. Evaluating future tying arrangements in AI through the rule-of-reason approach will allow for this.

Consumer Protection and AI

In addition to investigating and prosecuting unfair methods of competition, the FTC Act Section 5(a) also empowers the agency to target "unfair or deceptive acts or practices affecting commerce," thus bestowing on it a consumer-protection mission.[221] This allows it to seek injunctions against unfair or deceptive business practices and civil penalties against wrongdoers who have violated FTC consumer-protection rules.[222] Section 18 of the FTC Act empowers the FTC to pass substantive rules governing or proscribing unfair or deceptive trade practices.[223] An advantage of this provision is that it allows the FTC to seek civil penalties against wrongdoers;[224] a disadvantage is that Section 18 imposes lengthy "hybrid rulemaking" requirements,[225] making it a "slow and cumbersome" process.[226] Alternatively, the FTC may try to pass substantive consumer-protection and unfair-methods-of-competition rules under the FTC Act Section 6(g). Recent scholarship, however, strongly indicates that courts would hold that the FTC does not have the power to promulgate such formal rules.[227]

AI technology and its potential misuse or abuse raise a range of consumer-protection issues. The FTC has flagged concerns around data privacy raised by the vast amounts of data collection enabled by AI models and necessary to facilitate the development of such models.[228] There are also concerns that AI-enabled tools could facilitate existing online harms, including fraud, bias against protected groups, speech suppression, and copyright infringement.[229] For instance, AI tools that facilitate content moderation could inadvertently or purposely capture and suppress speech and opinion. If a government website uses tools that produce this result, it could violate the US Constitution's First Amendment.[230] Bias, censorship, and discrimination can also result from issues with AI training data, such as misclassification or mislabeling based on erroneous judgments by employees who lack sufficient training.[231] These adverse outcomes can also result from the inadvertent introduction of the data scientists' biases, or from flaws in the algorithms' designs.[232] Ultimately, practices that violate consumer-protection law or rules raise legal liability, whether they are facilitated by AI tools or manually performed by humans. When promulgating new consumer-protection rules or legislation, policymakers, regulators, and the FTC should weigh the costs, benefits, and impact on consumer protection and innovation. Additional rules can increase compliance costs for businesses,[233] which may be passed on to consumers; one example might be companies' adding fees for existing services—services that used to be free. Such costs can deter investment in developing and providing better products and services.

Restrictions on user data collection (or rules that increase the cost of data collection) may limit the ability to train foundation models and could especially hurt small AI start-ups that do not already have access to large proprietary data sets. The concepts section of this primer notes that future shortages in data for training models are likely, and that small data strategies for making the most of existing data without the need to collect new user data come with problems and may be insufficient. Companies affected by data collection and privacy rules and restrictions may find it harder to monetize user engagement. Where data collection is permitted with consent, imposing a rule that requires an affirmative-consent prompt may not be preferable to simply requiring data-collection policies to be readily available and accessible to the user, since the former can adversely affect user experience without meaningfully increasing privacy protection. Similarly, requiring firms to disclose details about the specific tools or applications that their anonymized data will be used to train, rather than simply disclosing that data will be collected and used to develop future products, can limit innovation because future uses and innovations may not be known at the time of data collection. Cumbersome or costly rules could also make the United States a less favorable environment for future AI investment and innovations, thereby increasing the comparative advantage of competitor economies, such as China's, for incubating future AI innovations.

Additional consumer-protection rules should also not be drafted over-broadly or ambiguously. Consider, for instance, California's Age-Appropriate Design Code Act (AB 2273 or AADC). The AADC attempts to protect minors by deterring and punishing the use of dark patterns in websites and digital platforms. It defines dark patterns as "user interface[s] designed or manipulated with the substantial effect of subverting or impairing user autonomy, decision-making, or choice."[234] Scholars note that AI can be used to study user preferences, mental traits, and behavior to design and implement more effective dark patterns.[235] The AADC bans online services (a) from using these to entice or encourage minors to supply personal information (i.e., in excess of what is reasonably expected for delivering the service) and (b) from taking any action that the service provider knows, or has reason to know, is materially detrimental to the mental or physical health of the minor.[236] Though the AADC may be based on a worthy goal, dark-patterns enforcement under that statute could be interpreted as encapsulating many widely used and potentially benign algorithmic features, such as newsfeed and auto-play functionality on social media and video platforms as well as tailored content recommendations.[237] This creates uncertainty for businesses, which is further exacerbated by the legislation's failure to set specific standards for what will be considered "materially detrimental." For instance, an algorithm that gathers and analyzes data to ascertain whether the user is a minor and should thus face content restrictions based on age could be deemed a materially detrimental dark pattern, thereby reducing minors' access to content that may or may not be considered age-appropriate by a judge or regulator.

CONCLUSION

AI poses a range of challenges for antitrust enforcers. US antitrust law remains a flexible, pragmatic tool that has been successfully adapted to emerging technologies by judges under the long-established CWS that has supported innovation. Abandoning this standard to incorporate an aversion to large businesses and to introduce extraneous factors, such as labor rights, environmental regulation, and special small-business protections, would politicize antitrust enforcement, increase costs and uncertainty for businesses, and inhibit innovation.

Antitrust enforcement agencies should be mindful of the potential for AI to harm the competitive process and consumers. At the same time, agencies should appraise costs and benefits while focusing on pragmatic, narrowly tailored solutions when calibrating enforcement approaches. Horizontal and vertical mergers, the use of AI-driven algorithms, and business strategies that harm competitors but not consumers or competition all have the potential to increase vigorous competition and benefit innovation and consumers. Business practices should be judged on a case-by-case basis by applying the rule of reason to specific markets where there is a potential for concrete, plausible consumer harm, avoiding false positives for anticompetitive conduct. Similarly, attempts to block mergers should be made on a selective basis that recognizes the agencies' limited resources and the potential for procompetitive efficiencies. Merger-enforcement initiatives should be undertaken when it is likely that the postmerger entity will have both the incentive and the ability to engage in anticompetitive unilateral or coordinated conduct; it is best to eschew a singular focus on superficial metrics, such as market or industry concentration, that may be immaterial to competition and consumer welfare. This approach to antitrust and consumer protection will ensure that the United States remains a robust and competitive market for the development of cutting-edge AI technology while mitigating its potential and actual harms.

NOTES

1. See, e.g., Ashima Rout et al., "Cognitive Function of Human Memory Using Machine Learning," in *Intelligent Systems: Proceedings of ICMIB 2020*, ed. Siba K. Udgata, Srinivas Sethi, and Satish N. Srirama (Singapore: Springer, 2021), 403–11.

2. There are already projects underway to create an "artificial general intelligence" with "the ability to achieve a variety of goals, and carry out a variety of tasks, in a variety of different contexts and environments." See McKenna Fitzgerald, Aaron Boddy, and Seth D. Baum, "2020 Survey of Artificial General Intelligence Projects for Ethics, Risk, and Policy," Global Catastrophic Risk Institute, December 31, 2020. Conversely, the vast majority of AI projects are focused on specific applications, such as the image generator DALL-E, or the inference engine ChatGPT. See Matt Mittelsteadt, "Artificial Intelligence: An Introduction for Policymakers" (Mercatus Policy Research, Mercatus Center at George Mason University, Arlington, VA, February 16, 2023).

3. Mittelsteadt, "Artificial Intelligence."

4. Vast amounts of venture capital are being poured into the global generative AI sector—an estimated $15.2 billion in the first half of 2023 alone. See Anna Cooban, "AI Investment Is Booming. How Much is Hype?," *CNN*, July 23, 2023.

5. Even large tech companies often struggle to attract and retain top talent. For instance, all eight Google scientists who authored a seminal 2017 paper on the architecture of large language models (or LLMs, a subset of foundation models) no longer work for the company. See Madhumita Murgia, "Transformers: The Google Scientists Who Pioneered an AI Revolution," *Financial Times*, July 23, 2023.

6. Mittelsteadt, "Artificial Intelligence," 8.

7. Mittelsteadt, "Artificial Intelligence"; Rishi Bommasani et al., "On the Opportunities and Risks of Foundation Models," *arXiv*, revised July 12, 2022. The proposed US Artificial Intelligence Transparency Act of 2023 defines foundation models as "artificial intelligence model[s] trained on broad data, generally [using] self supervision, generally [containing] at least 1,000,000,000 parameters, . . . applicable across a wide range of contexts, and [exhibiting or capable of being easily modified to exhibit] high levels of performance at tasks that could pose a serious risk to security, national economic security, national public health or safety, or any combination of those matters." See AI Foundation Model Transparency Act of 2023, HR 6881, 118th Cong. (2023).

8. Mittelsteadt, "Artificial Intelligence"; see Jason Brownlee, "Difference Between Algorithm and Model in Machine Learning," *Machine Learning Mastery* (blog), April 28, 2020.

9. Ramin Javan, and Navid Mostaghni, "AI-Powered Hyperrealism: Next Step in Cinematic Rendering?," *Radiology* 310, no. 1 (January 30, 2024).

10. Jun-Jie Zhu, Jinyue Jiang, Meiqi Yang, and Zhiyong Jason Ren, "ChatGPT and Environmental Research," *Environmental Science and Technology* 57, no. 46 (2023): 17667–70.

11. Marco Cascella et al., "The Breakthrough of Large Language Models Release for Medical Applications: 1-Year Timeline and Perspectives," *Journal of Medical Systems* 48, no. 1 (2024): 1–11.

12. Ziquan Liu et al., "Improved Fine-Tuning by Better Leveraging Pre-Training Data," *Advances in Neural Information Processing Systems* 35 (2022): 32568–81.

13. Liu et al., "Improved Fine-Tuning."

14. UK Competition and Markets Authority, "AI Foundation Models: Initial Report," September 18, 2023.

15. UK Competition and Markets Authority, "AI Foundation Models."

16. UK Competition and Markets Authority, "AI Foundation Models."

17. UK Competition and Markets Authority, "AI Foundation Models."

18. There are concerns that the increasing data demands of larger foundation models could lead to a scarcity of data in the future, thereby increasing its cost. See Pablo Villalobos et al., "Will We Run out of Data? An Analysis of the Limits of Scaling Datasets in Machine Learning," *arXiv* preprint arXiv:2211.04325 (2022).

19. UK Competition and Markets Authority, "AI Foundation Models."
20. UK Competition and Markets Authority, "AI Foundation Models."
21. UK Competition and Markets Authority, "AI Foundation Models."
22. UK Competition and Markets Authority, "AI Foundation Models."
23. For example, some startups can obtain investment in the form of credits from larger companies to spend on cloud-computing services. See UK Competition and Markets Authority, "AI Foundation Models," footnote 123, on AWS bActivate for Startup, Founders, and Entrepreneurs (amazon.com).
24. Jennifer Cobbe, Michael Veale, and Jatinder Singh, "Understanding Accountability in Algorithmic Supply Chains," in FAccT '23: Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency (New York: Association for Computing Machinery, 2023), 1186–97.
25. Microsoft Corporate Blogs, "Microsoft and OpenAI Extend Partnership," (blog), January 23, 2023.
26. Anthropic, "Anthropic Partners with Google Cloud," February 3, 2023.
27. Mittelsteadt, "Artificial Intelligence: An Introduction."
28. Mittelsteadt, "Artificial Intelligence: An Introduction."
29. Kathryn Wojtkiewicz, "How Do You Solve a Problem like DALL-E 2?," *The Journal of Aesthetics and Art Criticism* 81, no. 4 (Fall 2023), 454–67.
30. Mittelsteadt, "Artificial Intelligence: An Introduction."
31. Mittelsteadt, "Artificial Intelligence: An Introduction."
32. Merriam-Webster.com Dictionary, "Algorithm" (noun), accessed October 31, 2023, https://www.merriam-webster.com/dictionary/algorithm; Matt Mittelsteadt, "Artificial Intelligence."
33. Mittelsteadt, "Artificial Intelligence," 21.
34. Mittelsteadt, "Artificial Intelligence."
35. Mittelsteadt, "Artificial Intelligence."
36. "How Much Training Data Is Required for Machine Learning Algorithms?," *Cogito Tech* (blog), July 9, 2019; see also Mittelsteadt, "Artificial Intelligence."
37. Sébastien Bubeck and Mark Sellke, "A Universal Law of Robustness via Isoperimetry," *Microsoft Research*, December 1, 2021. See also Mittelsteadt, "Artificial Intelligence."
38. Guillaume Wenzek et al., "CCNet: Extracting High Quality Monolingual Datasets from Web Crawl Data," in ed. Nicoletta Calzolari et al., Proceedings of the Twelfth Language Resources and Evaluation Conference (European Language Resources Association, 2020), 4003–12, https://aclanthology.org/2020.lrec-1.494.pdf; see also Mittelsteadt, "Artificial Intelligence."
39. Suriya Gunasekar et al., "Textbooks Are All You Need," *arXiv* (June 20, 2023).
40. For instance, OpenAI negotiated an agreement with the Associated Press (AP) in July 2023 to license a share of its news archives as training data in return for OpenAI providing product and technology expertise. See Matt O'Brien, "ChatGPT-Maker OpenAI Signs Deal with AP to License News Stories," *AP*, July 13, 2023. Similarly, Google has engaged in meetings with news outlets in the United Kingdom, such as NewsUK and the Guardian, about using news data to train its generative AI models. See Cristina Criddle et al., "AI and Media Companies Negotiate Landmark Deals over News Content," *Financial Times*, June 17, 2023. See also UK Competition and Markets Authority, "AI Foundation Models."
41. Mittelsteadt, "Artificial Intelligence."
42. Mittelsteadt, "Artificial Intelligence," 22.

43. Mittelsteadt, “Artificial Intelligence”; Madhumita Murgia, “Why Computer-Made Data is Being Used to Train AI Models,” *Financial Times*, July 19, 2023.

44. Artificial data can lead to “model collapse” because it usually reproduces content that is more common in the original training data without retaining combinations of content (such as words and tokens) that are less frequently found in the training data set. For this reason, retraining models repeatedly on artificial data can lower variation in the model’s output to the point that the output loses relevancy to the user. See Ilia Shumailov et al., “The Curse of Recursion: Training on Generated Data Makes Models Forget,” *arXiv*, May 31, 2023. See also UK Competition and Markets Authority, “AI Foundation Models.”

45. Husanjot Chahal, Helen Toner, and Illya Rahkovsky, “Small Data’s Big AI Potential,” (Analysis, Center for Security and Emerging Technology, Washington, DC, September 2022). See also Mittelsteadt, “Artificial Intelligence.”

46. Mittelsteadt, “Artificial Intelligence.”

47. Piyush Verma and Stelios Diamantidis, “What Is Reinforcement Learning?,” *Synopsys*, updated April 27, 2021, https://www.synopsys.com/ai/what-is-reinforcement-learning.html. See also Mittelsteadt, “Artificial Intelligence.”

48. M. Tim Jones, “Models for Machine Learning,” IBM Developer, December 5, 2017. See also Mittelsteadt, “Artificial Intelligence.”

49. Mittelsteadt, “Artificial Intelligence.”

50. “What Is a Data Warehouse?,” Oracle, accessed October 31, 2023, https://www.oracle.com/database/what-is-a-data-warehouse.

51. Xu Chu et al., “Data Cleaning: Overview and Emerging Challenges,” in SIGMOD ’16: Proceedings of the 2016 International Conference on Management of Data (June 2016), 2201–6.

52. Daniel Haas, Jiannan Wang, Eugene Wu, and Michael J. Franklin, “CLAMShell: Speeding Up Crowds for Low-Latency Data Labeling,” *Proceedings of the VLDB Endowment* 9, no. 4 (2015): 372–83.

53. Husanjot Chahal, Ryan Fedasiuk, and Carrick Flynn, “Messier than Oil: Assessing Data Advantage in Military AI,” (Analysis, Center for Security and Emerging Technology, Washington, DC, July 2020). See also Mittelsteadt, “Artificial Intelligence.”

54. *Encyclopedia Britannica Online*, 2022, s.v. “semiconductor,” accessed February 2024, https://www.britannica.com/science/semiconductor; Mittelsteadt, “Artificial Intelligence.”

55. Mittelsteadt, “Artificial Intelligence.”

56. Mittelsteadt, “Artificial Intelligence.”

57. Mittelsteadt, “Artificial Intelligence.”

58. *Encyclopedia Britannica Online*, s.v. “Moore’s Law,” updated February 26, 2024, https://www.britannica.com/technology/Moores-law.

59. Saif M. Kahn, “AI Chips: What They Are and Why They Matter,” (Analysis, Center for Security and Emerging Technology, Washington, DC April 2020. See also Mittelsteadt, “Artificial Intelligence.”

60. Jennifer Prendki, “Why the End of Moore’s Law Means the End of Big Data as We Know It,” *Alectio*, March 27, 2020. See also Mittelsteadt, “Artificial Intelligence.”

61. For example, many chips today use a technique called speculative execution to boost speed. However, the complexity of the technique has made these chips vulnerable to cyberattacks known as transient execution CPU vulnerabilities. As a result, nearly every device that uses Windows, macOS, iOS, or Linux operating systems are vulnerable, and hardware-based vulnerabilities like this are costly and difficult to resolve because they usually require physical modification of the device. See also Mittelsteadt, “Artificial Intelligence.”

62. Peeyush Mathur and Nikhil Nishchal, “Cloud Computing: New Challenge to the Entire Computer Industry,” *2010 First International Conference on Parallel, Distributed and Grid Computing (PDGC 2010)*, (IEEE, Solan, India, October 2010): 223–28.

63. Nasser Taleb and Elfadil A. Mohamed, "Cloud Computing Trends: A Literature Review," *Academic Journal of Interdisciplinary Studies* 9, no. 1 (2020): 91–104.

64. UK Competition and Markets Authority, "AI Foundation Models."

65. UK Competition and Markets Authority, "AI Foundation Models."

66. John C. Eustice, "Understand the Intersection between Data Privacy Laws and Cloud Computing" *Thompson Reuters*, accessed February 2024, https://legal.thomsonreuters.com/en/insights/articles/understanding-data-privacy-and-cloud-computing.

67. Alden F. Abbott, "US Antitrust Laws: A Primer" (Mercatus Policy Brief, Mercatus Center at George Mason University, Arlington, VA, 2021).

68. Sherman Act, ch. 647, 26 Stat. 209 (1890) (current version at 15 U.S.C. §§ 1–7); See Standard Oil Co. of New Jersey v. United States, 221 U.S. 1 (1911).

69. Eastman Kodak Co. v. Image Technical Services, Inc., 504 U.S. 451, 466 (1992).

70. Cal. Dental Ass'n v. FTC, 526 U.S. 756, 775 n.12 (1999).

71. United States v. Grinnell Corp., 384 U.S. 563 (1966).

72. United States of America v. Microsoft Corporation, 253 F.3d 34 (D.C. Cir. 2001).

73. The Supreme Court describes the "rule of reason" analysis framework under the Sherman Act as follows: "[T]he plaintiff has the initial burden to prove that the challenged restraint has a substantial anticompetitive effect that harms consumers in the relevant market . . . if the plaintiff carries its burden, then the burden shifts to the defendant to show a procompetitive rationale for the restraint . . . [i]f the defendant makes this showing, then the burden shifts back to the plaintiff to demonstrate that the procompetitive efficiencies could be reasonably achieved through less anticompetitive means." See Ohio v. Am. Express Co., 138 S. Ct. 2274, 201 L. Ed. 2d 678, 2284 (2018). An "anticompetitive effect" is harm to the competitive process, not merely a showing of a negative impact on a component of market performance, such as increased prices. See: Gregory J. Werden, *The Foundations of Antitrust* (Durham, NC: Carolina Academic Press, 2020), 246–47.

74. Christopher S. Yoo, "The Enduring Lessons of the Breakup of AT&T: A Twenty-Five Year Retrospective," *Federal Communications Law Journal* 61, no. 1 (2008).

75. Clayton Act, ch. 323, 38 Stat. 730 (1914) (current version at 15 U.S.C. §§ 12–18, 19, 21–27).

76. See the Hart-Scott-Rodino Antitrust Improvements Act of 1976, Pub. L. 94-435.

77. See the Robinson–Patman Act of 1936, Pub. L. No. 74-692, 49 Stat. 1526.

78. Federal Trade Commission Act, ch. 311, 38 Stat. 717 (1914) (current version at 15 U.S.C. §§ 41–58).

79. FTC v. Cement Institute, 333 U.S. 683, 690 (1948).

80. Neil W. Averitt, "The Meaning of 'Unfair Methods of Competition' in Section 5 of the Federal Trade Commission Act," *Boston College Law Review* 21, no. 2 (1980), 227–300. See, e.g., Fashion Originators' Guild v. FTC, 312 U.S. 457, 464 (1941); Adolph Coors Co. v. FTC, 497 F.2d 1178, 1187 (10th Cir. 1974), cert. denied, 419 U.S. 1105 (1975); Mytinger & Casselberry, Inc., v. Federal Trade Commission, 301 F.2d 534, 539 (D.C. Cir. 1962) (decided on alternative grounds); Carter Carburetor Corp. v. Federal Trade Commission, 112 F.2d 722, 734 (8th Cir. 1940) (decided on alternative grounds). See also United States v. St. Regis Paper Co., 285 F.2d 607, 612 (2d Cir. 1960), aff'd 368 U.S. 208 (1961).

81. Some scholars argue that the prohibition on unfair methods of competition cannot punish solicitation of per se unlawful agreements, such as invitations to collude, price fix, or rig bids. See Gregory J. Werden, "Unfair Methods of Competition under Section 5 of the Federal Trade Commission Act: What Is the Intelligible Principle?" (Mercatus Working Paper, Mercatus Center at George Mason University, Arlington, VA, May 2023). However, the FTC has achieved several consent agreements banning what it deems to be "invitations to collude"—e.g., U-Haul Int'l, Inc., 150 F.T.C. 1 (2010); Va-

lassis Communications, Inc., 141 F.T.C. 247 (2006); Stone Container Corp., 125 F.T.C. 853 (1998); Precision Moulding Co., 122 F.T.C. 104 (1996); YKK (USA), Inc., 116 F.T.C. 628 (1993); A.E. Clevite, 116 F.T.C. 389 (1993); Quality Trailer Products Corp., 115 F.T.C. 944 (1992).

82. See Unlawful Restraints and Monopolies, S.Rep. No. 63-698, at 2 (1914). See also Fashion Originators' Guild of America v. FTC, 312 U.S. 457, 463 (1941), where the Supreme Court extended the prohibition on unfair methods of competition to acts that violate the public policy of the Sherman and Clayton Acts.

83. Alden F. Abbott, "US Antitrust Laws: A Primer."

84. Reiter v. Sonotone Corp., 442 U.S. 330, 343 (1979).

85. Verizon Communications Inc. v. Law Offices of Curtis V. Trinko, LLP (02-682) 540 U.S. 398 (2004), 305 F.3d 89.

86. Herbert J. Hovenkamp, "Is Antitrust's Consumer Welfare Principle Imperiled?," *Journal of Corporation Law* 45, no. 1 (2019): 65–94.

87. Herbert J. Hovenkamp, *Federal Antitrust Policy: The Law of Competition and Its Practice*, 6th ed. (St. Paul, MN: West Academic, 2020), 102.

88. Herbert J. Hovenkamp, "Predatory Pricing under the Areeda-Turner Test," *University of Iowa Legal Studies Research Paper*, no. 1506 (2015).

89. Jefferson Parish Hosp. v. Hyde, 466 U.S. 2 (1984).

90. Brooke Group Ltd. v. Brown & Williamson Tobacco Corp., 509 U.S. 209 (1993).

91. In Supreme Court jurisprudence during the 1960s, a merger would be deemed presumptively anticompetitive if the merged entity encapsulated over 30 percent of the relevant market; see United States v. Philadelphia Nat'l Bank, 374 U.S. 321 (1963). Conversely, more recent cases consistently recognize that market-concentration figures in isolation say little or nothing about whether the postmerger entity will raise prices and restrict output, reduce innovation, or otherwise leave consumers worse off without being undercut by competitors or new market entrants. These factors are best measured through alternative metrics and an understanding of the specific features and competitive dynamics of the relevant market. See Douglas H. Ginsburg and Joshua D. Wright, "Philadelphia National Bank: Bad Economics, Bad Law, Good Riddance," *Antitrust Law Journal* 80, no. 2 (2015): 377–96.

92. The notion of a systematic, causal relationship between market concentration and performance measures, such as prices and margins, is empirically unfounded; see Timothy J. Muris, "Improving the Economic Foundations of Competition Policy," *George Mason Law Review* 12, no. 1 (2003): 4, 5, 10. Instead, empirical evidence finds that even in highly concentrated markets, a significant number of mergers result in lower prices, thus benefiting consumers; see Vivek Bhattacharya, Gastón Illanes, and David Stillerman, "Merger Effects and Antitrust Enforcement: Evidence from US Consumer Packaged Goods" (NBER Working Paper No. 31123, National Bureau of Economic Research, Cambridge, MA, December 2023).

93. Mike Scarcella, "Microsoft Wins Dismissal of Gamers' Suit over $69 Billion Activision Deal," *Reuters*, March 21, 2023.

94. For instance, in high-technology sectors, it is recognized that even patented innovations often contain features that can be replicated without violating the patent, so that competitors are not excluded from competing even if a rival that owns the patent decides to raise the cost for others to acquire it. See William Rinehart, "Are 'Killer Acquisitions' by Tech Giants a Real Threat to Competition?," (Research in Focus, The Center for Growth and Opportunity at Utah State University, Washington, DC, October 2023).

95. Christopher S. Yoo, "The Post-Chicago Antitrust Revolution: A Retrospective," *University of Pennsylvania Law Review* 168, no. 7 (2020): 2145–69.

96. Yoo, "The Post-Chicago Antitrust Revolution."

97. Yoo, "The Post-Chicago Antitrust Revolution."

98. Yoo, "The Post-Chicago Antitrust Revolution."

99. Yoo, "The Post-Chicago Antitrust Revolution."

100. Chase Foster and Kathleen Thelen, "Brandeis in Brussels? Bureaucratic Discretion, Social Learning, and the Development of Regulated Competition in the European Union," *Regulation and Governance* (December 2023).

101. Council of Economic Advisers, Issue Brief, "Benefits of Competition and Indicators of Market Power," April 2016.

102. Carl Shapiro, "Antitrust in a Time of Populism," *International Journal of Industrial Organization* 61, issue C (2018): 722. For a summary of evidence debunking neo-Brandeisian assumptions on market concentration, see The White House, The Council of Economic Advisers, "Economic Report of the President," February 2020, 199–226.

103. See Gregory J. Werden, "An Economic Perspective on the Analysis of Merger Efficiencies," *Antitrust*, Summer 1997.

104. White House, "Economic Report," 200.

105. This is more likely to happen when there are high barriers, significant costs, or low incentives for new firms to enter and contest the market. Gregory J. Werden and Luke M. Froeb, "The Entry Inducing Effects of Horizontal Mergers: An Exploratory Analysis," *The Journal of Industrial Economics* 46, no. 4 (1998): 525–43.

106. Nicolas Petit, "Innovation Competition, Unilateral Effects, and Merger Policy," *Antitrust Law Journal* 82, no. 3 (2019): 873–920.

107. Janusz A. Ordover, "Coordinated Effects in Merger Analysis: An Introduction," *Columbia Business Law Review*, no. 2 (2007): 411.

108. Mirt Demirer and Ömer Karaduman, "Do Mergers and Acquisitions Improve Efficiency: Evidence from Power Plants," Stanford University Graduate School of Business (October 27, 2022), https://www.ftc.gov/system/files/ftc_gov/pdf/demirerkaraduman.pdf.

109. For example, the FTC and Department of Justice noted in their 2006 merger guidelines that "Mergers between competing firms, i.e., 'horizontal' mergers, are a significant dynamic force in the American economy. The vast majority of mergers pose no harm to consumers, and many produce efficiencies that benefit consumers in the form of lower prices, higher quality goods or services, or investments in innovation." See US Department of Justice and Federal Trade Commission, *Commentary on the Horizontal Merger Guidelines*, 2006. A 2012 Spanish study found that "multinational firms acquire the most productive domestic firms, which, on acquisition, conduct more product and process innovation (simultaneously adopting new machines and organizational practices) and adopt foreign technologies, leading to higher productivity." It also found that "innovation upon acquisition is associated with the increased market scale provided by the parent firm." See Maria Guadalupe, Olga Kuzmina, and Catherine Thomas, "Innovation and Foreign Ownership," *American Economic Review* 102, no. 7 (2012): 3594–627.

110. Alison Oldale and Jorge Padilla, "For Welfare's Sake? Balancing Rivalry and Efficiencies in Horizontal Mergers," *Antitrust Bulletin* 55, no. 4 (2010): 953–91. The Supreme Court notes that "without barriers to entry into the market it would presumably be impossible to maintain supra-competitive prices for an extended time." See Cargill, Inc. v. Monfort of Colorado, Inc., 479 U.S. 104, 119–20 n.15 (1986).

111. Daniel P. O'Brien, and Steven C. Salop, "Competitive Effects of Partial Ownership: Financial Interest and Corporate Control," *Antitrust Law Journal* 67, no. 3 (1999): 559–614.

112. United States v. Philadelphia National Bank, 374 U.S. 321, 364 (1963).

113. Polypore International, 150 F.T.C. at 599–600.

114. Polypore International, 150 F.T.C.

115. United States v. General Dynamics Corp., 415 U.S. 486, 497–98 (1974).

116. Most modern industrial organization economists concur that the 30 percent presumption of illegality makes no economic sense. See Cristina Caffarra and Serge Moresi, "Issues and Significance Beyond US Enforcement," *MLex Magazine*, April–June 2010, 41, 42–43. As noted by Ginsburg et al., "The point is not that 30 percent is an outdated threshold above which to presume adverse effects upon competition; rather, it is that market structure is an inappropriate starting point for the analysis of likely competitive effects. Market structure and competitive effects are not systematically

correlated" (381). See Douglas H. Ginsburg and Joshua D. Wright, "Philadelphia National Bank: Bad Economics, Bad Law, Good Riddance," *Antitrust Law Journal* 80, no. 2 (2015): 377–96.

117. Joseph Farrell and Carl Shapiro, "Antitrust Evaluation of Horizontal Mergers: An Economic Alternative to Market Definition," *B.E. Journal of Theoretical Economics* 10, no. 1 (2010), Article 9, at 1, https://faculty.haas.berkeley.edu/shapiro/alternative.pdf.

118. Dennis W. Carlton and Jeffrey M. Perloff, *Modern Industrial Organization*, 4th ed. (London, England: Pearson, 2004), 268; Muris, "Improving the Economic Foundations of Competition Policy."

119. See, for example, Bhattacharya et al., "Merger Effects."

120. Harold Demsetz, "Two Systems of Belief About Monopoly," in eds. Harvey J. Goldschmid, H. Michael Mann, and J. Fred Weston, *Industrial Concentration: The New Learning* (Boston, MA: Little Brown & Co, 1974), 164, 166–67.

121. See the "Artificial Intelligence: Key Concepts and Components" and "Cloud Computing" sections in this paper.

122. See the "Artificial Intelligence: Key Concepts and Components" section in this paper.

123. Carl Shapiro, "The 2010 Horizontal Merger Guidelines: From Hedgehog to Fox in Forty Years," *Antitrust Law Journal* 77 (2010): 701–59.

124. This metric is known as the Gross Upward Pricing Pressure Index (GUPPI). See U.S. Department of Justice and Federal Trade Commission, *Horizontal Merger Guidelines*, August 19, 2010, § 2.1.3 (hereinafter "2010 Horizontal Merger Guidelines").

125. For a comprehensive critique of the 2023 FTC/DOJ draft merger guidelines, see Gregory J. Werden, "The Rule of Law and the Draft Merger Guidelines" (Mercatus Policy Brief, Mercatus Center at George Mason University, Arlington, VA, 2023).

126. Ginsburg and Wright, "Philadelphia National Bank," 394.

127. See Elyse Dorsey, "Deepening Fault Lines: Diverging Antitrust Enforcement at the DOJ and FTC," University of Virginia, November 29, 2023, https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4626230.

128. Jeffrey A. Sonnenfeld and Steven Tian, "The FTC's Antitrust Overreach Is Hurting US Competitiveness and Destroying Value" (commentary), *Yale Insights*, December 13, 2023.

129. Colleen Cunningham, Florian Ederer, and Song Ma, "Killer Acquisitions," *Journal of Political Economy* 129, no. 3 (2021): 649–702.

130. Cunningham et al., "Killer Acquisitions."

131. Cunningham et al., "Killer Acquisitions."

132. Cunningham et al., "Killer Acquisitions." The percentage of killer acquisitions cited, however, would seem rather low, particularly as these estimates may be subject to significant error.

133. William Rinehart, "Are 'Killer Acquisitions' by Tech Giants a Real Threat?".

134. See Alden Abbott and Andrew Mercado, "Pharmaceutical Merger Enforcement Should Be Supported by Evidence and Sound Economic Theory" (Mercatus Public Interest Comment to the Multilateral Pharmaceutical Merger Task Force, Mercatus Center at George Mason University, Arlington, VA, June 25, 2021).

135. Axel Gautier and Joe Lamesch, "Mergers in the Digital Economy" (CESifo Working Paper No. 8056, February 3, 2020).

136. Gautier and Lamesch, "Mergers in the Digital Economy."

137. Gautier and Lamesch, "Mergers in the Digital Economy."

138. Martin K. Perry, 1989. "Vertical Integration: Determinants and Effects," chapter 4 in *Handbook of Industrial Organization*, vol. 1, 183–255.

139. See Robert H. Bork, *The Antitrust Paradox: A Policy at War with Itself*, Basic Books, 287–88 (1978).

140. Ronald Coase, "The Nature of the Firm" (1937), reprinted in Ronald H. Coase, *The Firm, the Market, and the Law* (1988): "A firm will tend to expand until the cost of organizing an extra transaction within the firm becomes equal to the cost of carrying out the same transaction by means of an exchange on the open market or the costs of organizing another firm." See also William J. Kolasky and Andrew R. Dick, "The Merger Guidelines and the Integration of Efficiencies into Antitrust Review of Horizontal Mergers," *Antitrust Law Journal* 71, no. 1 (2003): 207–51.

141. Bork, *The Antitrust Paradox*, 226–27; Makan Delrahim, "'Harder, Better, Faster, Stronger': Evaluating EDM as a Defense in Vertical Mergers," *George Mason Law Review* 26 (2019): 1427.

142. Improvements in offerings in one market through incorporating strategic position, assets, and advantages in another market in a merged or vertically integrated entity are an example of synergies. See G. Bernile and E. Lyandres, "Merger Synergies Along the Supply Chain," *European Winter Finance Summit* 201, no. 1 (2010).

143. See, e.g., Continental Television v. GTE Sylvania, 433 U.S. 37, 54-55 (1977). Here, the Supreme Court recognized that vertical restraints on trade, including the kind enabled by vertical mergers or vertical integration, can be procompetitive and efficiency-generating. The court thus ruled that such restraints on trade are not illegal per se and should instead be evaluated under the rule of reason. This principle was affirmed in State Oil Co. v. Khan, 522 U.S. 3 (1997), and Verizon Communications Inc. v. Law Offices of Curtis V. Trinko, LLP, 540 U.S. 398 (2004).

144. Based on economic understanding, the 1984 and 2010 merger guidelines set out narrow conditions for challenging vertical mergers. See the DOJ's 1984 Merger Guidelines and the 2010 Horizontal Merger Guidelines § 2.1.3. See also Stephen C. Salop, "Invigorating Vertical Merger Enforcement," *The Yale Law Journal* 127, no. 7 (2018): 1964 (the author observes that vertical merger enforcement actions in the United States are relatively rare); and Bruce Hoffman, Bureau of Competition, Federal Trade Commission, "Vertical Merger Enforcement at the FTC," remarks at Credit Suisse 2018 Washington Perspectives Conference, January 10, 2018).

145. See Steven C. Salop and Daniel P. Culley, "Vertical Merger Enforcement Actions: 1994–2016," Charles River Associates, Insights, June 30, 2017, accessed February 2024, https://www.crai.com/insights-events/publications/vertical-merger-enforcement-actions-1994-2016/.

146. See, e.g., St. Luke's, 778 F.3d 775. In that case, the FTC focused on the horizontal overlap in the market for primary physicians, instead of the deal's vertical-merger aspects, which involved integrating a hospital with a physician's group.

147. Thomas J. Krattenmaker and Steven C. Salop, "Anticompetitive Exclusion: Raising Rivals' Costs To Achieve Power over Price," *Yale Law Journal* 96, no. 2 (Dec. 1986): 209–93.

148. See Katie Tarasov, "ASML Is the Only Company Making the $200 Million Machines Needed to Print Every Advanced Microchip. Here's an Inside Look," *CNBC*, updated March 23, 2022.

149. Consider, for instance, the AI-driven algorithms on media platforms like YouTube, where recommendations are based on analyzing past use data of individual users, as well as the relevance of potential results to user search queries and the uniqueness of potential results. See Paul Covington, Jay Adams, and Emre Sargin, "Deep Neural Networks for YouTube Recommendations," in Proceedings of the 10th ACM Conference on Recommender Systems (New York: Association for Computing Machinery, 2016), 191–98.

150. Salil K. Mehra, "Antitrust and the Robo-Seller: Competition in the Time of Algorithms," *Minnesota Law Review* 100 (2016): 1323–75.

151. Ariel Ezrachi and Maurice E. Stucke, *Virtual Competition: The Promise and Perils of the Algorithm-Driven Economy* (Cambridge, MA: Harvard University Press, 2016).

152. Ezrachi and Stucke, *Virtual Competition*, 39, 62.

153. Paolo Siciliani, "Should We Act ex post Against Tacit Collusion—and How?," *Journal of European Competition Law and Practice* 5, no. 5 (May 2014): 294–303.

154. Paolo Siciliani, "Tackling Algorithmic-Facilitated Tacit Collusion in a Proportionate Way," *Journal of European Competition Law and Practice* 10, no. 1 (2019): 31–35.

155. Ezrachi and Stucke, *Virtual Competition*, 39, 62

156. Siciliani, "Tackling Algorithmic-Facilitated Tacit Collusion," 31.

157. The FTC's recent lawsuit against Amazon alleges that the tech giant used an algorithm called Project Nessie to monitor rivals' prices for the same goods to ascertain where Amazon could still profit by raising prices on its own offerings without losing customers—thereby anticompetitively raising its own revenue and profits at consumer expense through restricting output relative to price. Conversely, Amazon asserts that Project Nessie was an attempt to ensure that its competitive strategy of matching competitor prices remained sustainable in the long term. See Dana Mattioli, "Amazon Used Secret 'Project Nessie' Algorithm to Raise Prices," *Wall Street Journal*, October 3, 2023. Further factual analysis would be necessary to discern the accuracy of either narrative.

158. See US Department of Justice, "Former E-Commerce Executive Charged with Price Fixing in the Antitrust Division's First Online Marketplace Prosecution," press release, April 6, 2015. Margrethe Vestager, Commissioner, European Commission, "Algorithms and Competition," remarks at the Bundeskartellamt 18th Conference on Competition, Berlin, March 16, 2017, see Union, E., 2017. Algorithms and Collusion-Note from the European Union, v. 14.06. 2017, abrufbar unter https://one. oecd. org/document/DAF/COMP, 7.

159. Leegin Creative Leather Products, Inc. v. PSKS, Inc., 551 U.S. 877, 886 (2007).

160. See U.S. v. Socony-Vacuum Oil Co., 310 U.S. 150, 218 (1940): "a combination [of competitors] formed for the purpose and with the effect of raising, depressing, fixing, pegging, or stabilizing the price of a commodity in interstate or foreign commerce is illegal per se."

161. Meyer v. Kalanick, 174 F. Supp. 3d 817, 822 (S.D.N.Y. 2016).

162. Matthew Kassel, "Beware Algorithms That Could Collude on Prices," *Wall Street Journal*, April 1, 2019.

163. See, e.g., U-Haul Int'l, Inc., 150 F.T.C. 1 (2010); Valassis Communications, Inc., 141 F.T.C. 247 (2006); Stone Container Corp., 125 F.T.C. 853 (1998); Precision Moulding Co., 122 F.T.C. 104 (1996); YKK (USA), Inc., 116 F.T.C. 628 (1993); A.E. Clevite, 116 F.T.C. 389 (1993); Quality Trailer Products Corp., 115 F.T.C. 944 (1992). In contrast, Section 1 of the Sherman Act, which is enforced by the Justice Department, requires actual agreements among competitors to collude—mere invitations to collude, without a positive response, are insufficient to establish Section 1 liability.

164. Gregory J. Werden, "Unfair Methods of Competition."

165. United States v. American Airlines, Inc., 743 F.2d 1114 (5th Cir. 1984).

166. United States v. Ames Sintering Co., 927 F.2d 232, 235–36 (6th Cir. 1990).

167. Brooke Group Ltd. v. Brown & Williamson Tobacco Corp., 509 U.S. 209, 227 (1993).

168. See Bell Atlantic Corp. v. Twombly, 550 U.S. 544, 554 (2007): "The inadequacy of showing parallel conduct or interdependence, without more, mirrors the ambiguity of the behavior: consistent with conspiracy, but just as much in line with a wide swath of rational and competitive business strategy unilaterally prompted by common perceptions of the market."

169. Steven Berry, Martin Gaynor, and Fiona Scott Morton, "Do Increasing Markups Matter? Lessons from Empirical Industrial Organization," *Journal of Economic Perspectives* 33, no. 3 (2019): 44–68.

170. See Clamp-All Corp. v. Cast Iron Soil Pipe Institute, 851 F.2d 478, 484 (1st Cir. 1988).

171. In re Text Messaging Antitrust Litigation, 782 F.3d 879 (7th Cir. 2015); Theatre Enterprises v. Paramount Film Distribution Corp., 346 U.S. 537, 538 (1954).

172. Antonio Capobianco, Pedro Gonzaga, and Anita Nyeső, Organisation for Economic Co-operation and Development, "Algorithms and Collusion – Background Note by the Secretariat" (internal document), June 9, 2017.

173. Yavar Bathaee, "The Artificial Intelligence Black Box and the Failure of Intent and Causation," *Harvard Journal of Law and Technology* 31, no. 2 (2018): 890–938.

174. Ai Deng, "What Do We Know About Algorithmic Tacit Collusion?," *Antitrust* 33, no. 1 (Fall 2018).

175. Deng, "What Do We Know About Algorithmic Tacit Collusion?," 32.

176. Joshua P. Davis and Anupama K. Reddy, "AI and Interdependent Pricing: Combination Without Conspiracy?," *Competition* 30, no. 2 (2020): 1–17.

177. Michal S. Gal and Niva Elkin-Koren, "Algorithmic Consumers," *Harvard Journal of Law and Technology* 30, no. 2 (2017): 309–53.

178. Davis and Reddy, "AI and Interdependent Pricing."

179. Davis and Reddy, "AI and Interdependent Pricing."

180. Timothy J. Muris, "The FTC and the Law of Monopolization," *Antitrust Law Journal* 67, no. 3 (2000): 693–723. The Supreme Court describes monopolization as "the willful acquisition or maintenance of [monopoly] power as distinguished from growth or development as a consequence of a superior product, business acumen, or historic accident." See United States v. Grinnell Corp., 384 U.S. 563, 570–71 (1966).

181. Daniel Francis, "Making Sense of Monopolization: Antitrust and the Digital Economy," *Antitrust Law Journal* 84, no. 3 (2022): 779–839.

182. Brooke Group Ltd. v. Brown & Williamson Tobacco Corp., 509 U.S. 209 (1993).

183. Brooke Group, 509 U.S. at 232–33.

184. Brooke Group, 509 U.S. at 226. The court noted that "predatory pricing schemes are rarely tried, and even more rarely successful."

185. Brooke Group at 224.

186. United States v. Trans-Mo. Freight Ass'n, 166 U.S. 290, 320 (1897).

187. United States v. Colgate & Co., 250 U.S. 300, 307 (1919).

188. Verizon Communications Inc. v. Law Offices of Curtis V. Trinko, LLP, 540 U.S. 398, 408 n.3 (2004).

189. For further discussion on "raising rivals' costs," see the subsection on Vertical Mergers. Erik Hovenkamp, "The Antitrust Duty to Deal in the Age of Big Tech," *Yale Law Journal* 131, no. 5 (2021).

190. Verizon Communications Inc. v. Law Offices of Curtis V. Trinko LLP, 540 U.S. 398, 407–08 (2004).

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193. Hovenkamp, "The Antitrust Duty," 1492.

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195. Stephen Nellis, "Amazon Announces New Cloud AI Chip as Microsoft Rivalry Intensifies," *Reuters*, November 28, 2023.

196. Pranay Kotasthane and Abhiram Manchi, *When the Chips Are Down: A Deep Dive into a Global Crisis* (New Delhi, India: Bloomsbury India, 2023).

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204. Thomas H. Au, "Anticompetitive Tying."

205. Dennis W. Carlton and Jeffrey M. Perloff, *Modern Industrial Organization*, 4th ed. (London, England: Pearson, 2005), 201.

206. Illinois Tool Works Inc. v. Independent Ink, Inc., 126 S. Ct. 1281, 1288 (2006).

207. Herbert Hovenkamp et al., "IP and Antitrust: An Analysis of Antitrust Principles applied to Intellectual Property Law" (New York: Wolters Kluwer), § 21.5, at 21–113 to 21–115.

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209. Jefferson Parish Hospital District No. 2 v. Hyde, 466 U.S. 2, 12-8 (1984).

210. United States Steel Corp. v. Fortner Enterprises, 429 U.S. 610 (1977).

211. Michael E. Levine, "Price Discrimination Without Market Power," *Yale Journal on Regulation* 19, no. 1 (2002): 8.

212. Wells Real Estate, Inc. v. Greater Lowell Board of Realtors, 850 F.2d 803, 815 (1st Cir. 1988).

213. Mozart Co. v. Mercedes-Benz of North America, Inc., 833 F.2d 1342, 1348–51 (9th Cir. 1987).

214. The Supreme Court so held in Illinois Tool Works, Inc. v. Independent Ink, Inc., 547 U.S. 28 (2006).

215. Brief for the United States as Amicus Curiae Supporting Petitioners, Illinois Tool Works, Inc. v. Independent Ink, Inc., 126 S. Ct. 1281 (2006) (No. 04-1329).

216. Brief for the United States as Amicus Curiae Supporting Petitioners, Illinois Tool Works, Inc. v. Independent Ink, Inc.

217. See United States v. Microsoft, 253 F.3d 34 (Microsoft II) (D.C. Cir. 2001).

218. United States v. Microsoft, at 87.

219. United States v. Microsoft, at 95.

220. United States v. Microsoft, at 88–89.

221. Richard J. Gilbert, "Antitrust Reform: An Economic Perspective," *Annual Review of Economics* 15 (2023): 151–75; FTC Act, Section 5(a).

222. Federal Trade Commission, "A Brief Overview of the Federal Trade Commissions Investigative, Law Enforcement, and Rulemaking Authority," revised May 2021.

223. FTC Act, Section 18.

224. Kurt Walters, "Reassessing the Mythology of Magnuson-Moss: A Call to Revive Section 18 Rulemaking at the FTC," *Harvard Law and Policy Review*, 16 (2021): 519–79.

225. The statutory rulemaking requirements include (a) "FTC Publishes Advanced Notice of Proposed Rulemaking (ANPR) for Public Comment"; (b) "FTC Publishes Notice of Proposed Rulemaking (NPR) Seeking Public Comment"; (c) "informal hearings" (including rebuttal and cross-examination when there are disputed issues); (d) "FTC publishes Final Rule"; (e) "judicial review"; and (f) "rule enforcement" (which may lead to litigation as to to whether a rule actually applies to a particular factual situation). Kelley Drye & Warren LLP, "The FTC's Magnuson-Moss Rulemaking Process—Still an Uphill Climb," *JD Supra*, January 11, 2022. See also Administrative Conference of the United States, "Hybrid Rulemaking Procedures of the Federal Trade Commission" (adopted June 7–8, 1979).

226. Rohit Chopra and Lina M. Khan, "The Case for "Unfair Methods of Competition" Rulemaking," *The University of Chicago Law Review* 87 no. 2 (2020), Article 4.

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228. See, for example, Sara Gerke and Delaram Rezaeikhonakdar, "Privacy Aspects of Direct-to-Consumer Artificial Intelligence/Machine Learning Health Apps," *Intelligence-Based Medicine* 6 (2022), Article 100061.

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230. American Library Association, "First Amendment and Censorship," updated October 2021, https://www.ala.org/advocacy/intfreedom/censorship.

231. Federal Trade Commission, "Combatting Online Harms Through Innovation: A Report to Congress," June 2022, 6.

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234. Cal. Civ. Code § 1798.140(l).

235. Nathalie de Marcellis-Warin et al., "Artificial Intelligence and Consumer Manipulations: From Consumer's Counter Algorithms to Firm's Self-Regulation Tools," *AI and Ethics* 2 (2022), 259–68.

236. Cal. Civ. Code § 1798.99.31(b)(7).

237. See Katharine Miller, "Cannot Unsubscribe? Blame Dark Patterns," *Stanford University Human-Centered Artificial Intelligence*, December 13, 2021.

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