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Big Data is the topic for three of the articles in this issue: a roundtable conversation with practitioners, economists, and U.S. agency officials; an analysis of the use of automatic pricing algorithms; and a discussion by economists of some practical considerations practitioners may encounter as a result of larger and more diverse data sets. This issue also features an interview with Director Wu of China’s SAMR, and an in-depth analysis of the FTC’s DraftKings/FanDuel investigation.

Interview with Wu Zhenguo, Director General of China’s State Administration for Market Regulation (SAMR)
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Interview with Wu Zhenguo, Director General of China’s State Administration for Market Regulation (SAMR)

Editor’s Note: China’s new antitrust agency, the SAMR, formed earlier this year, merged three former Chinese antitrust agencies into one. In this interview, Mr. Wu Zhenguo, the Director General of this newly formed agency, discusses the progress of the restructuring and consolidation of the agencies, the future legislation plan and enforcement focus of the new agency, the impact of the U.S.-China trade relationship on antitrust enforcement, and other hot topics. DG Wu was formerly the Director General of the Anti-Monopoly Bureau under the Ministry of Commerce. He has written extensively on China’s anti-monopoly law, including an article published in the 2008 China symposium issue of the Antitrust Law Journal, entitled Perspectives on the Chinese Anti-Monopoly Law, 75 Antitrust L.J. 73 (2008). This interview was conducted in writing by Antitrust Source editor Fei Deng and Yizhe Zhang.

THE ANTITRUST SOURCE: Why did China go through a restructuring and consolidation of the Chinese antitrust agencies?

DIRECTOR GENERAL WU ZHEN GUO: Since the Anti-Monopoly Law (AML) came into force in 2008, the three anti-monopoly enforcement agencies have fulfilled different responsibilities during the AML enforcement based on their respective duties and functions, with the National Development and Reform Commission (NDRC) in charge of price-related conduct, the Ministry of Commerce (MOFCOM) responsible for reviewing concentrations of undertakings, and the State Administration of Industry and Commerce (SAIC) handling non-price-related conduct, including monopoly agreements, abuse of market dominance, and abuse of administrative power to restrict or eliminate competition. These three agencies have carried out effective work, but in the process of law enforcement, some inherent problems, such as function overlap and enforcement inconsistency occurred, which adversely influenced the uniformity and authoritativeness of antitrust enforcement, and was not conducive to the maintenance of fair market competition nor to the safeguarding of consumers’ interests.

In accordance with the Decision of the CPC Central Committee on Deepening the Reform of the Party and State Institutions, and the Plan on Deepening the Reform of the Party and State Institutions adopted at the Third Plenary Session of the 19th Central Committee of the Communist Party of China, as well as the Plan for the Institutional Restructuring of the State Council adopted at the First Meeting of the Thirteenth National People’s Congress, the Chinese government decided to set up the State Administration of Market Regulation (SAMR) to consolidate the antitrust enforcement duties originally performed respectively by the three agencies mentioned above, as well as the functions of the Anti-Monopoly Commission Office under the State Council. SAMR now is the sole antitrust enforcement agency and will undertake the general operation of the Anti-Monopoly Commission of the State Council, which will overcome the previous issue of function overlap and increase the efficiency of AML enforcement.

ANTITRUST SOURCE: What is the current status of the restructuring and consolidation? What are
the functions and organizations of the anti-monopoly Bureau (AMB) of SAMR and the specific duties of different divisions under the AMB?

**DG WU ZHENGUO:** Pursuant to the SAMR’s “three provisions” (*Provisions on the Functions, Structure and Staffing of the State Administration for Market Regulation*), SAMR set up the anti-monopoly bureau (AMB) to take charge of AML enforcement. At present, the institutional reform at the national level of the SAMR has been completed, and the local AML enforcement agencies’ reformation and consolidation is in progress. The main functions of the AMB are as follows: (1) to coordinate the implementation of competition policies; (2) to draft anti-monopoly rules and guidelines; (3) to organize the anti-monopoly law enforcement, including anti-monopoly reviews of undertaking concentrations, enforcement concerning restrictions or eliminations of competition through monopoly agreements, abuse of market dominance, or abuse of administrative power; (4) to provide guidance for enterprises in response to overseas anti-monopoly litigation; (5) to handle international cooperation of antitrust enforcement and information exchange; and (6) to undertake the daily operation of the Anti-Monopoly Commission of the State Council.

At present, there are ten divisions under the AMB, seven of which are responsible for case handling, with functions spanning ex ante prevention and interim and ex post supervision. The table below lays out the specific functions and duties of each division. With this setup, we will strive to optimize the functionality, improve the law enforcement and authorization mechanism, improve the consistency of antitrust enforcement, and achieve a consistent, unified, authoritative, and efficient antitrust enforcement system.

<table>
<thead>
<tr>
<th>Divisions</th>
<th>Functions and Duties</th>
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<tbody>
<tr>
<td>Competition Policy and International Cooperation Division</td>
<td>Supporting legislation, publicity, training and international cooperation affairs.</td>
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<tr>
<td>Monopoly Agreement Investigation Division</td>
<td>Investigating and handling monopoly agreement cases.</td>
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<tr>
<td>Abuse of Dominance Investigation Division</td>
<td>Investigating and handling cases involving abuse of market dominance.</td>
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<tr>
<td>Administrative Monopoly Investigation Division</td>
<td>Investigating and handling cases involving abuse of administrative power to restrict or eliminate competition.</td>
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<tr>
<td>Merger Control Divisions</td>
<td>Consisting of three divisions—Division 1, Division 2 and Division 3—respectively in charge of reviewing mergers of different industries.</td>
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<tr>
<td>Law Enforcement Supervision Division</td>
<td>Investigating illegally implemented mergers and supervising the enforcement of merger remedies.</td>
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<tr>
<td>Anti-Monopoly Coordination Division</td>
<td>Undertaking the daily work of the Anti-monopoly Commission Office of the State Council.</td>
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**ANTITRUST SOURCE:** Please describe the impact of the reform of the antitrust enforcement agencies on the actual practice of antitrust enforcement.

**DG WU ZHENGUO:** The enforcement of the Anti-Monopoly Law is now under the sole responsibility of the SAMR, eliminating the previous issue of overlapping functions among the three former antitrust enforcement agencies, and is therefore conducive to building a unified, authoritative, and efficient antitrust enforcement system.
According to China’s AML, the power of enforcement of the AML is reserved to the anti-monopoly enforcement agency under the State Council. This serves to ensure the consistency of the enforcement of the AML and to build a unified, open, competitive and orderly market system throughout China.

Meanwhile, under Article 10(2) of the AML, the anti-monopoly enforcement agency under the State Council may, when needed, delegate work to the corresponding agencies at the provinces, autonomous regions, or municipalities to conduct relevant antitrust enforcement. In order to make up for the lack of staff at the national level, we are drawing on experiences concerning the setup of law enforcement agencies from jurisdictions such as Europe and the United States, to construct an appropriate mechanism for delegation with proper guidance and supervision, and consistent enforcement standards, and to formulate fair, open, and transparent market rules while resolutely preventing and overcoming local protectionism and market segmentation. By further improving the system and mechanism of antitrust enforcement, we can promote the comprehensive and effective implementation of the AML.

Since its establishment, the AMB has engaged in various efforts to protect fair market competition, strengthen the implementation of competition policies, put a fair competition review system in place, and has made further progress in antitrust enforcement, breaking regional blockades and industry monopolies, maintaining a fair competition market environment, and protecting consumers’ welfare. This year, up to the present time, a total of 14 cases of suspected monopoly agreements and 17 cases of suspected abuse of market dominance have been filed, spanning industries such as pharmaceuticals, automobiles, electronics, semiconductors, materials, and public utilities; 20 cases of abuse of administrative power have been handled and concluded; 412 notifications of undertaking concentrations have been received, of which 363 cases have been filed and 355 cases have been concluded; and 12 cases of failure to notify have been penalized and disclosed.

ANTITRUST SOURCE: Is there any plan for new legislation after the consolidation is finalized? We understand that in the area of mergers, the rules established by MOFCOM have already been updated, but with minor changes. Is there any plan to integrate and update the rules related to monopoly agreements and abuse of dominance previously established by the NDRC and the SAIC? Will the AMB or the Anti-Monopoly Commission introduce new rules and guidelines?

DG WU ZHENGUO: With respect to legislation, we are going to further improve the AML enforcement mechanism and fully bring the anti-monopoly work in line with the rule of law. We will push forward the amending of the AML and the enactment of implementing legislation, completing the enactment, amendment, and abolishment of the implementing laws and rules of the three former anti-monopoly enforcement agencies, and further improving the transparency and predictability of law enforcement.

Specifically, first, in the areas of regulating monopoly agreements, abuse of market dominance and administrative monopolies, we will develop uniform substantive rules and procedural requirements. We will integrate the Provisions Against Price Fixing of the NDRC with the Provisions for the Industry and Commerce Administrations on the Prohibition of Monopoly Agreements and the Provisions for the Industry and Commerce Administrations on the Prohibition of Abuse of Dominant Market Position of the SAIC, integrate the Provisions on the Administrative Procedures for Law Enforcement Against Price Fixing of the NDRC with the Provisions on the Procedures for the Administrative Departments for Industry and Commerce to Investigate and Handle Cases of
Monopoly Agreements and Abuse of Dominant Market Position of the SAIC, as well as formulate the Provisions on the Administrative Procedures for the Prohibition of Abuse of Administrative Power for the Purpose of Eliminating or Restricting Competition, the Provisions on the Prohibition of Abuse of Administrative Power for the Purpose of Eliminating or Restricting Competition and other new provisions, so as to unify the enforcement standards and procedures, resolve the problem of overlapping functions among the former anti-monopoly enforcement agencies, and provide clearer guidance.

Second, the Anti-Monopoly Commission will publish four guidelines as soon as possible, namely the Anti-Monopoly Guidelines for Intellectual Property Rights, the Anti-Monopoly Guidelines for the Automobile Industry, the Guidelines for Application of the Leniency Regime to Cases of Horizontal Monopoly Agreements and the Guidelines for Undertakings’ Commitments in Anti-Monopoly Cases, in an effort to share our law enforcement ideas and experience with business operators, stabilize their expectations, and improve the transparency of law enforcement.

Third, we will focus on promoting the amendment of the AML, taking all considerations in mind, in order to improve the existing legal provisions so they may be adapted to the development and changes of both the national and global economic environments.

ANTITRUST SOURCE: In terms of mergers, how would you summarize the experience that China's antitrust agencies have gained over the past ten years? What further developments will be expected in the future?

DG WU ZHENGUO: This year marks the 10th anniversary of the enforcement of the AML. As of October this year, China’s antitrust agencies have handled and concluded 2,420 notifications of concentration of undertakings in total, among which 2,380 were unconditionally approved, two were forbidden, and 38 were conditionally approved. Some high-profile cases have attracted widespread attention both within China and globally, including prohibitions against Coca Cola’s acquisition of Huiyuan Company, and against the establishment of NetworkCenter by Maersk, MSC and Dafei Group, as well as conditional approvals on Microsoft’s acquisition of Nokia’s equipment and service business, Dow’s merger with DuPont, and Google’s acquisition of Motorola Mobility, LLC. The enforcement of such cases is beneficial to the maintenance of an effective competition pattern and fair market competition. In terms of the process of concentration reviews, the enforcement agencies have continuously reformed and improved the review mechanism, strictly adhered to fair and civilized enforcement, constantly streamlined the concentration notification filing procedure, strengthened the implementation of the simple case review system, established a routine for handling cases electronically, and refined the mechanism of identifying and categorizing more complicated cases from less complicated ones. Consequently, enforcement efficiency has been significantly enhanced and enforcement transparency has been greatly improved.

Over the past decade, the antitrust review of concentrations of undertakings in China has come a long way in terms of forming a sophisticated conceptual framework, choosing appropriate enforcement approaches, and developing mature enforcement skills. The following experiences deserve continuing adherence in our future enforcement and will lead and guide our anti-monopoly enforcement work.

First is to abide by the principles of fairness and justice, which are essential to the maintenance of a fair competition environment. In the course of anti-monopoly enforcement, we treat all entities of all types equally, ensure the fair participation of all entities in market competition, and protect
the legal rights and interests of the parties according to the law. We carry out an information disclosure system to guarantee the fairness and transparency of anti-monopoly enforcement.

Second is to strive for professionalism and efficiency. This is also the key to earning reputation and respect from our international colleagues. We put great emphasis on strengthening theoretical support, and routinely adopt economic analysis tools to improve the professionalism and scientific nature of our enforcement work. We also make substantial efforts to optimize case handling mechanisms and consistently improve enforcement efficiency, which resulted in an increase of more than 85 percent in review efficiency over the past ten years. After the introduction of the notification system for simple cases, over 97 percent of simple cases have been concluded within 30 days.

Third is to maintain an open mind and be cooperative. This has helped us cope with challenges arising from globalization and improved our own capabilities and enforcement expertise. We have signed antitrust cooperation memoranda with around 28 jurisdictions, including the European Union, the United States, Canada, Japan, Russia, and South Africa, and have carried out enforcement cooperation in dozens of major cross-border merger and acquisition cases to jointly maintain fair competition in the global market. Furthermore, we have also included a special chapter concerning competition policy and antitrust enforcement in free trade treaties and economic and commercial cooperation agreements to promote investment and trade liberalization.

As the next step, we will further strengthen the streamlined merger review process. We shall not only ensure that major cases in key areas are properly handled, but also adhere to due process during antitrust enforcement in general. First of all, we should handle cases in a lawful, fair, and civilized manner according to laws to maintain fair market competition. Second, we must persist in protecting consumer welfare, and in strengthening enforcement in areas relating to people's livelihood, including education, medical care, and public utilities, to satisfy the growing needs of the people for better quality of life. Third, we must further improve the efficiency and professionalism of concentration review and apply economic analysis tools more widely so as to improve the scientific and objective nature of antitrust enforcement and to make sure the enforcement is appropriate, reasonable, and justified. Fourth, we should strengthen competition supervision in the area of newly emerging markets, adhere to the principles of tolerance and prudence, properly handle the relationship between innovation stimulation and fair competition maintenance, follow the market rules, and avoid casual and excessive intervention, so as to create a fair competition market environment for the sustainable and healthy growth of the newly emerging markets.

ANTITRUST SOURCE: Please brief us on the cooperation between Chinese antitrust enforcement agencies and foreign competition authorities during the review of significant cross-border merger transactions.

DG WU ZHENGUO: In recent years, along with the increasing globalization of economies and competition among businesses, anti-monopoly enforcement has become a common presence in countries with established market economies, and development of international competition rules has gained increasingly wide attention. Conflicts arising from inconsistency among the development of national economies, individual businesses’ goals, and the legislation, enforcement, and judicial practices in various countries, become the key driving force facilitating cooperation among various jurisdictions in antitrust enforcement and international competition regulation.

China’s anti-monopoly enforcement agencies have given high priority to the international exchanges on and cooperation in competition policies and anti-monopoly enforcement. We have
negotiated and entered into more than 50 cooperation documents with competition authorities across nearly 30 countries and regions, such as the United States, the European Union, and Australia. We have worked with the antitrust enforcement agencies in various jurisdictions, including the United States and the European Union, in dozens of actual cases of merger antitrust review. We have set up arrangements for competition policy and antitrust enforcement cooperation in eight free-trade agreements (FTAs), including the China-Switzerland FTA, and are in the process of setting competition policies in several other FTAs, to promote the alignment of competition regulations around the world.

When working jointly with foreign enforcement agencies in the antitrust review of significant merger transactions, we have always operated under the framework established by the memorandum of understanding (MOU) signed with the respective foreign agency, and obtained in advance a waiver from the parties concerned. This is in line with international practice, and protects the privileged information of transaction parties, and such cooperation so far has operated smoothly, effectively, and efficiently. After ten years of enforcement, cooperation on individual cases has improved both in depth and in frequency, and mechanisms for routine exchange have been put in place. Take the example of the Dow-DuPont merger: we conducted altogether over 30 exchange sessions with our EU and U.S. counterparts during the review process, and held such exchange sessions nearly every week in the later stages to communicate the review progress and coordinate the review efforts and corresponding remedies, ensuring and facilitating the successful closing of the merger. The cooperation on Dow-DuPont was recognized as a “bilateral cooperation model” by the EU.

**ANTITRUST SOURCE:** What’s your opinion on the impact of the current Sino-U.S. trade relations on antitrust merger review?

**DG WU ZHENGUO:** I have heard rumors saying that, due to the Sino-U.S. trade war, China’s antitrust enforcement agencies have been extremely harsh on antitrust review of mergers involving U.S. companies, even willfully delaying or withholding the clearances. These remarks are irresponsible and not true. As can be observed from our quarterly release of statistics on transactions cleared unconditionally, a large number of transactions involving U.S. enterprises have been approved in a fast manner, some of which were even approved ahead of other jurisdictions, such as the European Union and the United States. In fact, the review approach taken by China is consistent with other jurisdictions, where only those transactions that have or may have the effect of eliminating or restraining competition require a longer review period. Meanwhile, the market circumstances may vary greatly across different countries, and antitrust enforcement agencies of different jurisdictions may focus on different competition issues. These factors could also impact the duration of review. Therefore, China’s anti-monopoly enforcement practice would never take the China-U.S. trade relation as a starting point, but would only consider the market competition conditions, the potential impact of the transaction on market competition, and safeguarding consumers’ interests.

China, as a major country in the world economy, takes its responsibilities seriously to safeguard enterprises of all types to compete on an even playing field, and create a rule of law, and a convenient and international business environment. China has always abided by the principle of fairness and justice in our antitrust reviews and concentrations. Looking ahead, we will continue to follow through on this principle and continue to treat all enterprises, including American companies, equally, so as to protect fair market competition, safeguard consumer interests, and promote the healthy development of a market economy.
**ANTITRUST SOURCE:** We have noticed that there is a divergence between the standards adopted in administrative and judicial enforcement with respect to vertical monopoly agreements. What is the AMB’s opinion on this?

**DG WU ZHENGUO:** Article 14 of the AML expressly prohibits undertakings from entering into monopoly agreements maintaining resale prices or setting minimum resale prices. As seen from the text of the provision, the above mentioned two behaviors are treated as per se illegal by the AML. In addition, according to Article 15 of the AML, the provisions of Article 14 are not applicable to certain resale price maintenance (RPM) agreements that satisfy the conditions listed in Article 15.

From an international perspective, nearly all the countries over the world have consistently adopted the approach of strictly prohibiting RPMs over the last 100 years since establishment of antitrust laws and regulations. In 2007, U.S. courts began to adopt a rule of reason approach in certain individual RPM cases. However, to date, RPMs are still deemed as per se illegal by many state courts in the United States. On the other hand, other major jurisdictions, including the European Union and Germany, all expressly prohibit RPM, with exemptions provided that certain conditions are met. In recent years, antitrust enforcement activities aimed at regulating RPM have been actively implemented in multiple jurisdictions, such as the European Union and Germany. Ever since the promulgation of the AML in China, the Chinese anti-monopoly enforcement agencies have prosecuted dozens of RPM cases in a variety of industries and sectors, such as premium liquor, infant milk powder, branded cars, home appliances, medical devices, and auto parts and components, and have effectively safeguarded fair market competition and consumer welfare. As demonstrated in the enforcement practices, RPM severely impeded the independent pricing activities of vendors, eliminated or restrained competition among distributors, drove up product prices, and prevented consumers from benefiting from effective competition, thus impairing social welfare. Meanwhile, the enforcement agencies also have taken into full consideration the justification of vertical price restraints based on evidence produced by undertakings involved in each specific case.

As for the next steps forward, the SAMR will continue to implement enforcement activities in accordance with the AML. For RPM, the enforcement agencies will grant exemptions thereto according to the AML, provided that the undertakings concerned can prove that the agreement falls within the scope of Article 15 of the AML and that the agreement will not significantly restrain competition in the relevant market but will enable consumers to benefit from it.

**ANTITRUST SOURCE:** Are there any enforcement precedents where exemptions of certain monopoly agreements were applied? Will the AMB propose to promulgate any further rules or guidance on the assessment of monopoly agreement exemptions?

**DG WU ZHENGUO:** As one of the most frequent and common monopolistic conducts, monopoly agreements could eliminate or restrain market competition, and impair consumers’ interests and social welfare. Like other major jurisdictions around the world, monopoly agreement has been a focus of anti-monopoly enforcement in China. Over the last ten years, China’s anti-monopoly enforcement agencies have prosecuted a large number of cases involving monopoly agreements in a variety of industries, such as power supply, chemicals, automobiles, electronics, and maritime transportation. Based on information collected in individual cases, China’s anti-monopoly enforcement agencies would not pursue further investigation and prosecution once they confirm that the
alleged monopoly agreement met the requirements set forth in the exemptions in Article 15 of the AML. In a case where the investigated parties failed to prove that their conduct fell within the scope of Article 15, the antitrust enforcement agencies would pursue prosecution in order to safeguard fair market competition and consumer interests. To guide and facilitate the lawful business operation of undertakings, we are now studying the enforcement procedures and factors to be considered in the granting of exemptions, to further clarify the specific requirements to qualify for exemptions.

**ANTITRUST SOURCE:** Will the AMB promulgate further guidance or regulations on standard-essential patents?

**DG WU ZHENGUO:** In recent years, there have been a considerable number of complaints on alleged monopolistic conducts involving standard-essential patents (SEPs), as some patentees of SEPs have allegedly abused their dominant market positions through conduct, such as charging unfairly high royalties, restricting dealings, and imposing unreasonable terms, which may impair fair market competition and consumer interests. Based on previous enforcement experiences, China’s anti-monopoly enforcement agencies drafted the *Guidelines on Anti-Monopoly Law Enforcement in Areas Involving Intellectual Property*. Factors laid out in the Guidelines to be considered in determining market dominance, relating to conduct, such as charging unfairly high prices, refusing to license, tying or bundling, and imposing unreasonable trading conditions, also apply to SEPs. Meanwhile, due to the unique characteristics of SEPs, distinct from other IP rights, competition issues related to SEPs in practice are more complicated. Along with jurisdictions such as the European Union and the United States, China pays great attention to antitrust regulation of SEPs. Based on previous enforcement experiences and extensive advice sought from all sectors, we will further strengthen investigation and research efforts to provide more specific guidelines for players in the relevant markets, in order to protect fair competition in SEPs.

**ANTITRUST SOURCE:** What are the priorities of the AMB in the foreseeable future? Are there certain industries that China’s antitrust enforcement will be particularly focused on?

**DG WU ZHENGUO:** In the next stage, the AMB will mainly focus its antitrust enforcement efforts in the following areas.

First is to establish a unified, authoritative, and efficient AML enforcement system. We will build up both the central and local enforcement forces, continue to rationalize the law enforcement system and mechanisms, and enhance the capacity building of antitrust enforcement teams to ensure efficient AML enforcement. We will dedicate and allocate more resources to the local enforcement forces and form an optimized, coordinated, and highly efficient system. We will also bolster the building of the cooperation mechanism, by, on one side, further improving the internal working mechanism of the Anti-Monopoly Commission (AMC), as well as the communication and exchanges between the member agencies of the AMC to foster synergy effects and, on the other side, intensifying cooperation with other ministries and departments and efficiently utilizing the “external wisdom” to give full play to the roles of experts and think tanks.

Second is to proceed with antitrust enforcement in a routine, professional, and standardized manner. The antitrust enforcement agencies will maintain a tough stance towards law enforcement in all areas. Key areas of enforcement will be emphasized, especially in major industries and segments that impact fair competition and economic development. Such enforcement will set up role
models in driving and promoting the overall antitrust enforcement. In particular, we will strengthen enforcement efforts in areas such as education, medical, and public services, which are closely related to people’s daily lives. We will improve professionalism and standardization of enforcement by increasingly adopting economic analyses to improve the scientific foundations of our analyses. We will further standardize the enforcement procedures, limit the discretion of and inconsistency among enforcers, treat all entities of all types with fairness and justice, and strive to build an even playing field for market competition.

Third is to build a comprehensive, scientific, and efficient system. We will push forward in an expeditious way the amendment of the AML and its supporting legislation by taking into consideration our own national conditions as well as the extensive foreign experiences. We will continue the promulgation, revision, and annulment of the supporting regulations and rules of the three former anti-monopoly enforcement agencies and will promulgate and implement more anti-monopoly guidelines so as to further improve the transparency and predictability of enforcement and provide a regulatory framework for anti-monopoly enforcement. In addition, we will develop more diversified enforcement tools of competition policies.

Fourth is to protect, encourage, and promote innovation. An era of innovation-driven economy requires us to pay more attention to the innovation environment and digital economy. It is these businesses that play a key role in innovation. To enable innovation to become the primary driving force behind development, competition policies shall facilitate the fostering of an innovation-friendly environment and the protection of intellectual property in a balanced way, and shall adapt to developments in the economic environment and business models. We must resolutely break up the pattern of territorial fragmentation and industry monopolies to open up market space for innovation and entrepreneurship. Moreover, endeavors shall be made in the field of IP antitrust enforcement to guide the proper exercise of IP rights by business operators. In the supervision of the Internet industry, we should strive to build a fair competition market enabling sustainable and sound development of emerging economic industries.

Fifth is to deepen international exchanges and cooperation in competition policies and antitrust enforcement. We will continue to expand international antitrust cooperation in order to keep pace with the economic globalization and adapt to the growing trend of China’s opening-up to the world. We will not only cooperate with developed countries but also with the developing countries, especially the “Belt and Road Initiative” * countries, so as to jointly address the competition risks and challenges in the world. Meanwhile, we will deepen cooperation with the countries with established market economies by further bolstering the building of cooperation mechanisms and expanding the scope of enforcement cooperation in specific cases based on current experience. In addition, we will also focus more on the joint development of bilateral and multilateral systems of international competition regulation by strengthening consultations, dialogues, and mutual learning with foreign counterparts, so as to align and coordinate international competition regulations.

Sixth is to facilitate the prevalence of a competition advocacy approach and competition culture. We will proceed with the establishment of enterprise compliance systems, continue to advocate industry competition, and facilitate the prevalence of competition culture. Specifically, we will advance the construction of new AML think tanks with Chinese characteristics to create a signif-

* Editor’s note: The Belt and Road Initiative (BRI) (Chinese: 一带一路) is a development strategy adopted by the Chinese government involving infrastructure development and investments in countries in Europe, Asia, and Africa. See more details at http://english.gov.cn/beltAndRoad/.
icant platform with international influence. We will also continue to enhance the competition law awareness of market players and the public and to promote the recognition of the whole society towards fair competition and the concept of innovation and development, so as to provide a sound external environment for AML enforcement.

**ANTITRUST SOURCE:** As amendment of the AML has been on the agenda, can you tell us more about the progress to date?

**DG WU ZHENGUO:** Being the fundamental law designed to protect fair market competition, safeguard consumer interests, and promote the development of a market economy, the AML has been playing a significant role in preventing and restraining monopolistic conduct, protecting fair market competition, enhancing economic efficiency, safeguarding consumer welfare and public interest, and promoting the healthy development of the socialist market economy since its implementation in 2008. Due to developments in both the global economic environment and the Chinese economy, amendment to the AML is required as the current version cannot reflect these changes. For example, certain provisions are so general that they do not provide actual guidance in practice, thus triggering controversies in their application during actual enforcement; certain clauses are not well designed, limiting their legal effects; and certain liabilities are exceedingly heavy or exceedingly light, thus detrimental to the authority of law. Good law is the prerequisite for good governance. As the underlying law in a market economy, anti-monopoly law shall adapt to new situations, new changes, and new requirements.

The Anti-monopoly Commission of the State Council attaches great importance to the amendment of China’s AML and has included it in its work plan. We have developed four working principles to guarantee the solid implementation of amendment: first, to refine the legislative policies based on the rule of law, the latest law enforcement experiences, and competition policy; second, to conform to China’s own national conditions and current stage of economic development while referring to the established practices and experiences in developed countries; third, taking into full consideration the uncertainty of anti-monopoly laws, to maintain flexibility while regulating the discretion of law enforcement authorities; and fourth, to focus on the most pressing issues encountered during the enforcement practices.

In the early stage, according to the plans of the Anti-monopoly Commission of the State Council, we have organized an expert advisory group to conduct studies, extensively consulted with member entities of the Committee, and with relevant ministries, and departments, experts, enterprises, and legal attorneys, and have the research report and draft proposals in place. Based on the current studies, the most urgently needed amendments to the AML include areas such as further clarification on regulations of monopoly agreements, abuse of market dominance positions, the review procedure of concentration of undertakings, system design aimed at regulating administrative monopolistic conduct, and refinement of legal liabilities. At present, the AML amendments have been scheduled as the second priority of legislation items on the legislative agenda of the Standing Committee of the thirteenth National People’s Congress. For the next step, we will, based on the results achieved from the earlier stage, take into consideration China’s own national conditions, draw extensively on successful experiences from other jurisdictions, and focus on the primary complicated issues in practice, so as to push forward the AML amendments in an expeditious way.
Roundtable: Discussing the Big Picture on Big Data

Editor’s Note: On November 2, 2018, five distinguished panelists sat down with Kevin Christensen and Kevin Yingling, Editors on The Antitrust Source, to discuss the competitive significance of data and pricing algorithms. The panelists provided their views on such topics as how to define the term “big data,” why the topic of big data is receiving heightened attention in antitrust right now, how pricing algorithms trained on big data should be evaluated under the antitrust laws, whether data can form a barrier to entry, and how the collection of big data affects our thinking on the role of privacy in competition policy. The Roundtable was edited for publication.

KEVIN YINGLING: Thank you for talking with us about big data issues. All of you have either written or spoken about big data, so we are sure to have a very insightful discussion during this roundtable, and we are very interested to hear your thoughts on these topics.

Let’s start off with definitions so we have some clarity in what we’re talking about. In some of the academic literature, you see big data described as having four or five Vs: volume, velocity, variety, value and, sometimes, veracity.

Is that a sensible way to talk about big data? How do you think about “big data” when using that term?

JAMES COOPER: Yes, I think that’s right, the three to five Vs define it. Sometimes you also hear that a distinguishing feature of big data is that you’re looking at nearly the entire population, rather than merely a sample of the population.

I think that aside from the quantity, one of the things that distinguishes, say, working with big data from a normal data set is that it’s kind of rough. It’s not well structured, and often, you’re looking for associations between variables that emerge from the data, not necessarily for casual relationships.

1 The views expressed here are solely those of Dr. Cooper and do not purport to represent those of the Federal Trade Commission or any individual commissioner.
When you’re working with large data sets, it gives you the benefit of a lot of statistical power—the ability to detect small relationships that you can’t with a smaller data set. But the problem is you also can find a lot of spurious correlations. You look at any large data set, and if you play with it long enough, just by random chance you’re going to find associations.

Because of these issues, one must be able to apply some expertise when working with big data in order to derive the benefits. You have to know how to ask the right questions of the data, and interpret their answers.

**BARRY NIGRO:** One of my concerns with the term “big data” is that it’s a label, and sometimes is used as a conclusion to indicate that what you’re talking about is an entry barrier or something that facilitates monopolization and market power. I think when you label things and talk about them only in a general sense, there’s a danger that you will misunderstand the competitive significance.

On the one hand, it’s useful to put some parameters around what is meant by big data; on the other hand, I think it’s always important to keep in mind specifically what you’re talking about and the competitive significance of the asset on which you’re focused. It’s more productive to have a detailed discussion about the precise asset and its role in the competitive dynamics of the industry.

**TERRELL MCSWEEENY:** Big data is a term that gets thrown around to describe a lot of different features of data and the role it plays in the digital economy. In antitrust, we care a lot about specifics, and I think that’s appropriate.

We should be very mindful of what the competitive significance of data is when examining it through an antitrust lens. Very often, when people talk about big data, they are generalizing about data and its role in the digital economy.

**AI DENG:** I do think the definition of big data can be very helpful as a guide. When we look at the competitive effects, one thing that’s very important is to understand the role of big data in a particular industry. I often see people being unclear about whether big data is the output of an industry or a type of input that is used to improve their products and services. And I think that will be the first question that I would ask, if I am looking at competitive effects.

And if the big data turns out to be an industry output, it will be relatively straightforward to analyze. A lot of standard tools would apply. For example, we can ask how costly it is to procure, process, and host this data. But when the big data is used as an input, I think things are more subtle, and that is something we can discuss further today.

**DARREN TUCKER:** I think the four or five V definition is fine when you’re making general comments about data or the evolution of technology. But when you’re looking at the role of data in any particular industry or in a particular investigation or market study, it’s very important to move beyond a generic definition of data and look at the nature of the data at issue and how it is actually used.

For example, is it used as an input or is it the final product? If it’s used as an input, how important is it as an input into the final product? How widely available is the data to other potential entrants or companies in the industry? What’s the value or difficulty in obtaining historical data? Historical data has a lot of value for certain industries. In other cases, historical data has very little, if any, value.

We should be careful to avoid some assumptions that are sometimes made in this area. For example, the fact that an incumbent may use a lot of data is not necessarily an indication as to
the value of data to some other company or that data is a barrier to entry. Likewise, you often see an assumption that big data is used in a lot in digital online markets, but less so in traditional sectors. That’s probably not a good assumption. For example, some kinds of online advertising use virtually no personal data, whereas some traditional industries like retailers or insurance rely very heavily on big data.

In short, it’s important to move beyond assumptions about data and look carefully at its actual role and importance competitively for incumbents and for potential entrants.

KEVIN YINGLING: With the definitional work out of the way, let’s turn to why there is so much interest in big data now. The FTC is having hearings at American University in November that are going to be covering the topic, and there have been a lot of published works and conferences addressing big data issues. Why is the topic getting so much attention right now?

BARRY NIGRO: One of the reasons it’s getting a lot of attention is because people don’t completely understand it. There’s concern about how it’s used and how it’s acquired.

When I think about things that aren’t well understood, I sometimes translate them into something with which I am familiar. If you think about the type of data that a platform may acquire about customer preferences, that may be analogous to—in the old days—company customer files that record preferences and customer requirements. It’s hard for me to imagine, for antitrust reasons, the government or a court ordering that customer files be shared in order to give competitors equal access.

This goes back to the point I made earlier, when you’re talking about data, the context is important; understanding where the data resides in the competitive ecosystem and how it’s acquired and being used is critical. To some extent, there is a lack of familiarity and understanding of that now, which is why it’s a topic of conversation.

In addition, there’s the obvious point that data has become more prominent in the economy with everything being digitized and the ability to store more and more information at a lower cost.

JAMES COOPER: I think that data is such a hot topic in consumer protection and antitrust because it’s something that the large platforms have in common: they collect and use enormous amounts of consumer data. And their use of data has been front and center in some of the scrutiny they’ve come under recently on both the competition and consumer protection sides.

These discussions are one of the reasons the FTC is doing the series of hearings to look at the economy in the 21st century, the competition and consumer protection issues, and many of them revolve around data, not coincidentally because the largest companies in the economy tend to live on data.

DARREN TUCKER: The current focus on big data and algorithm issues in the antitrust world is somewhat surprising to me because the antitrust agencies have a lot of experience in these areas, going back decades. These are not novel issues for the agencies. The FTC and DOJ have been bringing what you might call big data cases at least since the ‘90s, if not earlier. And there’s been quite a number of them. The same thing is true at the European Commission—the Google/Double-Click case, for example. The same is true in the algorithm space. There have been court cases

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looking at potential Sherman Act Section 1 claims based on pricing algorithms in concentrated industries going back at least a decade.

Likewise, arguments that we should incorporate privacy or other non-competition considerations into antitrust are nothing new. The Supreme Court addressed this issue back in 1931 in *FTC v. Raladam Co.*

So, it’s a bit surprising to me that there’s debate on these issues now. It would have made more sense to have this debate maybe 20 or 25 years ago when antitrust concerns about these issues would have been more significant. For example, big data analysis at that time was largely limited to governments and large businesses because the cost of collection, storage, and processing was dramatically higher. Same thing with algorithms. Smaller companies can offer much more sophisticated pricing today than they could 10 or 20 years ago, which can be disruptive to efforts of collusion.

**TERRELL McSWEENY:** I agree that big data is not actually a new thing in markets. Antitrust enforcers have confronted the competitive significance of data for a very long time. What is, arguably, different about data today is the Vs point, especially the volume and velocity of it.

Certainly, it’s not by accident that people call the increasing digitization of previously analog businesses the fourth industrial revolution, because technology is changing many industries. Data is increasingly significant in a host of new ways in many areas.

So, in that sense, I think it’s completely appropriate for competition enforcers around the world to engage in a dialogue about whether competition laws and frameworks are keeping pace with the technological change that is occurring in the marketplace. Here in the United States, in particular, that examination is coming at a time when there is also a broader debate over the role and purpose of antitrust law. I think the reason this conversation is happening among antitrust enforcers now is due to both of those things—the rapid evolution of technology and the largely political debate over the scope of antitrust law.

An important feature of our antitrust framework is that enforcers, civil society, and the bar continually engage in dialogue and examination of it. A strength of our framework is that it is adaptable and flexible, and ought to be able to evolve along with the dynamic marketplace.

**AI DENG:** As an economist and someone who deals with data every day, I always think about data, along with the ability to analyze it.

A lot of the interest is due to the supercomputing power that we have today, the revolution in machine learning, artificial intelligence. It may appear that all of a sudden with the help of big data, with the computational power, with the advances in the artificial intelligence and machine learning community, machines can do a lot more. And I don’t think that’s something we have seen in recent history. It is natural for people outside of the research circle to feel excited and also uncertain about what machines can do. And I think that uncertainty contributes to some of the interest as well.

**BARRY NIGRO:** I want to follow up on a point Darren was making, and that is that the availability of data and our ability to analyze it have grown. That raises a question whether the competitive significance of data has increased or decreased since the ’90s. In other words, if you think about vol-
ume, one of the Vs, how many data points do you need to predict an outcome? At some point the marginal value of an additional data point declines rapidly; you don’t need more than a handful of data points to predict with a fair degree of confidence a particular outcome. It’s not clear to me, and this is a question of fact on which I don’t have a view, whether having a large volume of data makes a material difference when it comes to a firm’s ability to compete.

**AI DENG:** That’s a good question. And it goes back to why I think the definition of big data can be really helpful. We can look at the four dimensions, and we would ask which Vs are the relevant features, because they’re not always all relevant.

So, taking volume as an example, whether it is relevant is application- and industry-specific. For example, think about the standard machine learning tasks, say, image recognition, where you feed the machine a picture and then the machine will tell you what this picture is a cat or a dog. Typically, that kind of application would require a lot of data. Another example would be machine translation. You speak to the machine in one language and the machine would translate it into another.

If you look at other industries, let’s say online advertising, my observation is that they are more interested in real-time data. So it’s not necessarily the volume per se that matters. It’s about how timely the data are.

I do think that you ought to look at it as a fact-based analysis. And there’s not a single rule there.

**DARREN TUCKER:** For machine learning, labeled data is what’s really valuable, not random data. Random data can still be useful, but labeled data is much, much more useful, and that typically involves human time to generate.

To borrow Ai’s example, you could develop a machine learning program to identify cats and dogs in pictures. You will need to give it a series of pictures of different kinds of animals and objects to learn from. But first, some human has to go through and label which objects are the cats and dogs and which aren’t so the program can learn from these examples.

There are a lot of ways to get labeled test data for machine learning applications. Sometimes there’s publicly available data that companies can use, you can purchase it, or you can pay people to label data that you have.

As with other types of big data applications, machine learning often exhibits diminishing returns from the use of additional data. Also, the problems we are trying to solve using machine learning typically can also be addressed with techniques that do not involve machine learning. This reinforces the point that the need for data may vary considerably for different companies trying to solve the same problem.

There are also efforts to solve problems with machine learning using little or no data. That’s called reinforcement learning. Machines essentially train themselves. A good example of that is Google’s DeepMind team, which developed two different programs to play the Chinese game, Go. One of the programs learned from seeing how humans actually play. Another program learned just by playing itself over and over. And it turned out that the machine that was self-taught was the better player.

You’re seeing competition agencies start to confront some of these issues. For example, in the Microsoft/LinkedIn decision, the European Commission looked at what kind of data was needed.

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*Case M.8124—Microsoft/LinkedIn, Comm’n Decision (Dec. 6, 2016),* [http://ec.europa.eu/competition/mergers/cases/decisions/m8124_1349_5.pdf](http://ec.europa.eu/competition/mergers/cases/decisions/m8124_1349_5.pdf).
for CRM [customer-relationship management] machine learning. The Commission found that the data that LinkedIn had, while very valuable, was not essential and that other CRM suppliers could obtain relevant data from alternative sources.

**TERRELL McSWEENY:** If I could just pick up on a point that Darren is making, an essential feature of data, even in very sophisticated use cases like for training machine learning systems and increasingly autonomous systems, is that it is often readily available.

Data can often be non-rivalrous, which means it can be used by multiple companies at the same time, it’s publicly available, and relatively easy to gather. There are not necessarily a ton of barriers to the collection of the data that’s required to train these systems.

That said, I think we are seeing antitrust enforcers flag the question of access as an area of inquiry. What I hope enforcers continue to strive for here is a very factual understanding of the competitive significance of data so that they can reach the right answers to those questions.

**JAMES COOPER:** Jumping off what Barry and Ai said, I think it really is important to point out that it’s not so much the size of the data set, it’s what you do with it. Empirical work in economics has gotten much better over the past couple of decades, partly due to more data and more computing power, but also—and probably more importantly—because of clever research design that gets us closer to randomized control experiments. Having a good design is what allows one to draw causal inferences, which are so important in policy making.

To the point about big data and its competitive implications, you want to have access to good data, large amounts of data that are helpful in finding relationships and honing machine learning algorithms. But if you don’t have the right team in place and are not asking the right questions, you’re not going get useful answers.

For example, Hal Varian, Google’s Chief Economist, wrote in *Big Data, New Tricks for Econometrics*, that he has found a random sample of 0.1 percent works for analysis of business data. Having a billion data points but not having the team or the ability to figure out how to do the right test to get at the right answer is pretty useless. The really clever team with the small amount of data is probably more likely to lead their firm in the right direction.

**KEVIN YINGLING:** Let’s follow up on a topic that a number of you have already touched on, which is the issue of algorithmic collusion. Big data can be helpful in training these algorithms, and some commentators have suggested a concern about pricing algorithms and their ability to facilitate coordination or collusion.

Are those concerns legitimate? Even if there is no human coordination, do pricing algorithms using big data present a threat to competition?

**DARREN TUCKER:** The increasing use of pricing algorithms across industries and providers should be seen by antitrust authorities as a beneficial development, not as something that raises alarm bells. Pricing algorithms allow very rapid responses to competitive conditions and competitor actions. In other words, pricing algorithms facilitate efficiency in the marketplace, which we generally think of as procompetitive.

To turn to your question, a good starting point for assessing the potential for pricing algorithms to facilitate coordination is to look at what the empirical data show. Is there evidence that algorithms have actually facilitated collusion? Sophisticated pricing algorithms have been used for a few decades, at least by some firms. So, if we’ve had problems with algorithms facilitating either
tacit or explicit collusion, we should have some evidence by this point. And we don’t really have empirical evidence of those kinds of effects.

Now, there have been a handful of cases—for example, the DOJ and CMA [Competition and Markets Authority] brought the case against two poster sellers on Amazon Marketplace. But that was a fairly run-of-the-mill collusion case, where the parties got together as they normally do, agreeing not to compete on price, and the mechanism of collusion was the algorithm.

Likewise the Russian Federal Antimonopoly Service brought a case against the Russian subsidiary of a Korean manufacturer, involving vertical price fixing using an algorithm.5 But again, the algorithm was just used to monitor retail pricing. Once the manufacturer saw the retailer deviating from its recommended price, the manufacturer just picked up the phone or sent an email saying, “Hey, raise your price.”

So, we don’t really see a lot of evidence of algorithms facilitating coordination in the way that some have hypothesized.

Another way to approach the question is to consider how the adoption of pricing algorithms may affect the potential for coordination, looking at the usual factors. Complex pricing algorithms tend to reduce market transparency, which will tend to reduce the ability to coordinate. The reason is that pricing algorithms allow much more dynamic, differentiated, rapid pricing responses, which rivals are not necessarily going to see. A sophisticated pricing algorithm might allow a company to change prices hourly and have personalized pricing and discounts, which will be very hard for rivals to monitor.

There was an article in the Wall Street Journal about how most retailers, airlines, hotels, and financial companies have all developed these things called CLVs, which are customer lifetime value scores.6 These are proprietary scores each of these companies has developed using algorithms to measure the value of retaining a particular customer. Based on the score, we all get different prices, freebees, upgrades, and customer service—all of which is virtually impossible, if not impossible, for rivals to see.

In addition to decreased market transparency, the use of pricing algorithms may facilitate maverick behavior and reduce entry barriers due to the ability to price more accurately to particular customer segments. Pricing algorithms may also facilitate greater cost asymmetry and product differentiation, which makes coordination more difficult.

We are also seeing regulators using algorithms to identify problematic behavior. The FTC for many years has been monitoring wholesale and retail petroleum prices, using algorithms to identify unusual movement in the marketplace that might trigger closer attention. Similarly, the Brazilian and Korean competition agencies are monitoring specific industries for behavior that may look curious. I would not be surprised to see customers in some industries engaging in similar efforts to monitor their suppliers’ pricing through algorithms.

JAMES COOPER: There are some interesting papers out there that posit various models or hypotheticals of how algorithmic pricing could lead to explicit or tacit collusion. But it’s also important to remember that collusion at this scale is a really complex game-theoretic problem.

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Computing power is certainly available, but I think the jury is still out concerning whether, as a practical matter, it would be feasible to set up algorithms that would be able to sort signals from noise and figure out what the other algorithms are saying and coordinate prices in a way that is harmful to consumers.

I would be careful moving down a road that would apply the antitrust laws to a situation where prices that are set by algorithms appear to be moving together absent some evidence of an agreement. In Ethyl\(^7\) and Boise Cascade,\(^8\) courts rejected the FTC’s attempt to stretch Section 5 to cover the unilateral adoption of pricing practices, such as base point pricing or MFNs, under the theory that they facilitated tacit collusion in concentrated industries.

I would also echo some of the things that Darren talked about. Anything that reduces transaction costs is typically good for consumers. If you’ve got an algorithm that can make a pricing decision in a microsecond, which otherwise would take a marketing department a week or even a day to figure out, that’s probably a good thing.

So I think we should have a presumption that algorithmic pricing is likely to reduce transaction costs and probably increase competition. Now, again, this is a very new area and one worthy of study. Indeed, this topic will be part of an upcoming FTC hearing at Howard University. But I think we shouldn’t start off with the presumption that algorithmic pricing is likely to be harmful to competition based on conjectures. I’d rather start from the proposition that algorithm pricing is likely to be a good thing until evidence moves us off those priors.

**AI DENG:** Darren did a good job summarizing some of the issues related to algorithms. And it’s true that we haven’t seen a real case where you have autonomously colluding robots.

At the same time, I also think it’s helpful—and this is something that I have been doing over the past two years—to look into the AI literature and figure out what the AI researchers have been doing in terms of developing algorithms that could potentially collude autonomously. What’s interesting is that there is very active research going on in the machine learning and AI field, where algorithms that better coordinate and cooperate with opponents are being developed. In an article in the Fall issue of *Antitrust* magazine,\(^9\) I summarize some of the papers, all of which came out in the past two years. Based on this AI research, I would say there is already theoretical or experimental evidence that algorithmic tacit collusion could happen. To give you one example, a group of AI researchers has recently developed an algorithm that is akin to a hub-and-spoke type algorithm. Their AI agents include a planning agent, so it’s like the central hub. And this planning agent basically hands out punishments and rewards to make sure that the other agents learn to cooperate.

But there are several reasons I’m not overly concerned at this point. For one, there are many technical obstacles. I think James mentioned some—just the complexity of figuring out how to interact with others, how to elicit cooperation, presumably without explicit communication, without necessarily knowing other algorithm’s intent and behavior, and all that. As a result, the existing experimental studies are still based on very simple frameworks, on a very limited set of possible strategies that agents can take. And I laid out many more reasons in my article.

**TERRELL McSWEENY:** If I could just follow up on that point. I agree that at this point, it’s a highly the-

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\(^7\) E.I. du Pont de Nemours & Co v. FTC (Ethyl), 729 F2d 128 (2d Cir. 1984).

\(^8\) Boise Cascade Corp. v. FTC, 637 F2d 573 (9th Cir. 1980).

oretical problem—a bit like sci-fi antitrust, if you will. But the technology is evolving very rapidly and, as we’ve been discussing, one of the transformative aspects is the velocity at which systems can change.

It’s appropriate for competition enforcers to be on top of the literature in this area and for people who are in the antitrust bar to be thinking about it and to be helping clients navigate some of the potential challenges. For example, we know to be cautious about hub-and-spoke structures, and I think we understand much of the type of conduct that may be problematic. I think algorithms used for highly personalized pricing are probably unlikely to facilitate tacit coordination because of how challenging cheating might be in that environment, for example.

But in thinking about antitrust issues, it may be appropriate to consider what the long-term objectives are for a more autonomous system. If its objectives are very short term, then it will likely maximize price. But if it’s very long term, and it’s a very sophisticated system, then maybe the possibility is greater that it could edge towards coordination.

These are issues that competition lawyers should have on their radar. And, in addition to some of the research that Ai has just mentioned, some researchers have found it at least probable that algorithms in certain situations may end up engaging in coordinated behavior.

It’s great to have a wealth of different points of view out there, and there’s no agreement in the literature right now about it whatsoever, but I think it’s an important area for everybody to have on their screen.

BARRY NIGRO: I think the facts and the context matter. Looking at algorithms generally, I don’t see why they’re inherently anticompetitive, especially to the extent they facilitate more efficient pricing. If the structure of the market is such that it’s competitive, it’s not obvious why an algorithm would cause competitors to engage in a practice of raising price rather than continuing to compete aggressively.

Now, it could be that the use of algorithms may or may not, depending on the circumstances, facilitate tacit coordination in a market where consolidation is increasing rather than decreasing. Imagine that a vendor has a pricing algorithm, and they promote it on the basis that it will increase revenue by 10 percent: if you use our pricing algorithm, and by the way, in your local market you have three competitors, each of which has purchased the software so you will benefit from having it as well, and all of you will be able to raise revenue and be able to raise profits as a result of using the same pricing software. That raises some interesting questions as to whether it is a good thing, a bad thing, legal, or illegal. As when we were talking about big data, it’s hard to generalize; you need to think about the context in which the question is arising in order to properly understand and evaluate it.

DARREN TUCKER: Barry’s interesting hypothetical resembles a hub-and-spoke type of conspiracy theory. We have an existing framework to evaluate those types of claims, as we do for other potential algorithm-based concerns.

Beyond the merger context, I don’t think the Sherman Act can or should reach tacit collusion, whether it’s facilitated through algorithms or otherwise. As a general matter, parallel adoption of pricing algorithms is going to be outside the reach of the antitrust laws, even if that leads to interdependent pricing.

Even in markets with interdependent pricing, use of algorithms should, in my view, defeat an inference of conspiracy under Matsushita, even in the presence of plus factors. If your pricing

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is based on an algorithm, that shows pretty definitively that you are in fact, pricing independent-
ly, even if you wind up with pricing that looks very similar to your competitors. A case on point is
the LTL shipping services antitrust litigation from about a decade ago, which involved use of
identical software by two companies in the industry to determine fuel price surcharges, a highly
concentrated industry, and parallel behavior. The court dismissed the case because there was no
evidence of conspiracy; having two separate algorithms that reached the same outcome was
insufficient.

JAMES COOPER: Yes, just reacting a little bit to what Darren and Barry said, I certainly would agree
that antitrust should stay away from just conscious parallelism without an agreement. But going
back to Barry’s hypothetical, I think this is why antitrust is really up for the job of dealing with algo-
rithmic pricing.

You could imagine a situation where there is a software producer who says: “Hey, I’ve got this
algorithm, and I’ve fixed the problem of coordination. Just plug it in and you will be colluding with
your competitors. Your profits will go up!” But this scenario isn’t really that much different than say
DOJ’s Apple case or the Toys “R” Us case the FTC brought under a hub-and-spoke theory. You
would probably develop the same sort of evidence where you have the software provider giving
assurances that everyone is on board.

And I think that the important thing here again is that you can find an agreement under those sets
of facts. So, to reduce the risk of false positives, you want to be careful about going down a road
where now that we have algorithms, we don’t need to worry so much about showing agreement.

AI DENG: I made the same point in the forthcoming Antitrust magazine article I mentioned earlier.
In terms of what antitrust agencies and even private parties can do, there is a lot we can learn from
the current literature. Keep in mind that, as I just said, you do see evidence in the technical liter-
ature that algorithms are being developed to tacitly cooperate. But at the same time, developing
such algorithms turns out to be very challenging, for many reasons.

One lesson we can draw from that is the following. Suppose you have some rogue developers
who are trying to develop an algorithm to elicit tacit coordination. The chances are that there is a
paper trail, so that even without technical expertise, it may still be possible to for us to uncover a
lot of the evidence. It is common and in fact critical in any research to document research design
and findings. And such documents from the algorithm developers, I think, are going to be
extremely helpful in discovery or an investigation. You could potentially subpoena such docu-
ments and see exactly what they were trying to achieve when they were designing the algorithms.

Another type of document I also find relevant is the one that others just mentioned, the mar-
keting materials. If you just developed a collusive algorithm and you market it to your customers
by saying, “Look, if you buy this, you’re going to raise your profits because my algorithm learns
to cooperate with your competitors”—again, you don’t need technical expertise to uncover and
interpret such documents.

It’s also worth emphasizing that cartels come in different shapes and forms. In a lot of the indus-
tries, some collusive agreements, whether they are among humans or machines, are going to

13 Toys “R” Us, Inc. v. FTC, 221 F.3d 928 (7th Cir. 2000).
manifest themselves through what we call plus factors and super-plus factors. For example, let's say we have an industry that relies heavily on sales representatives. A cartel trying to either fix prices or allocate markets may need to instruct the sales reps to maintain pricing and stop going after others' business. This change is something one could observe ex post. And it does not matter whether the instruction comes from a machine or a human. I argued in the article that firms may have a hard time placing the blame on a machine in that case.

KEVIN CHRISTENSEN: We came close to an answer earlier but let me pose the question more directly: Can big data be a barrier to entry?

TERRELL McSWEENY: I think that we discussed, earlier in the conversation, how important facts are to that assessment. When it comes to antitrust law, facts and specificity matter. And the fact is that antitrust enforcers have been able to assess data as a barrier to entry when it is in fact a barrier to entry. I’m thinking here of cases like Nielsen-Arbitron14 and Reed Elsevier-ChoicePoint.15 We’ve seen both DOJ and the FTC accurately assess the competitive significance of data and make the right call in several cases in the last decade. We’ve also seen them accurately assess—as in the Microsoft/LinkedIn transaction—when data, even very large amounts of it, is not a barrier to entry.

DARREN TUCKER: I would agree with Terrell’s remarks. I do think that a lot of the debate in this area is on a somewhat different topic though, which is the claim that big data leads to a feedback loop. The argument goes that the collection of data will allow incumbents to improve their products, which attracts more people, particularly in markets with network effects, which allows them to collect even more data and so on and so on. The end result is that entry becomes extraordinarily difficult, if not impossible, because of the incumbent’s permanent data advantage. I think there are a lot of problems with that theory, and I don’t think that the agencies have bought into this theory. But you do see a vigorous debate in the literature on this point.

There are a number of reasons to be skeptical of this feedback loop theory. For one thing, data, by itself, doesn’t guarantee a good quality product, as we discussed before. There are lots of other inputs into a good product. For an online service, for example, there is engineering talent, there’s capital, there’s responsiveness, there’s an attractive user interface, and probably most important of all, just having a good idea.

Another reason to be skeptical of the feedback loop theory is that little, if any, data may be needed to enter and gain scale. Even when data is necessary, you can typically purchase it. There are hundreds of data brokers selling a wide range of personal and other data.

End users multihome. People typically use multiple search engines, multiple social networks, and multiple online retailers. Producers multihome as well. For example, a website may use a dozen or more different advertising and analytic services observing a user’s browsing session on the website. Both user and producer multihoming facilitates getting data to potential entrants or smaller competitors.

Platforms are typically differentiated. We typically don’t see like-for-like competition in the digital space, which means that new entrants can rely on differentiated data, to the extent that there’s even a need for data.

As Barry and Ai mentioned earlier, there are diminishing returns to data, so even if an incumbent has a lot of data, that doesn’t necessarily mean that it has much of an advantage over a new entrant.

We typically see congestion in two-sided markets where a lot of the concerns about big data arise. So, where you have platforms with lots of buyers and sellers for example, some sellers will want to go to a new platform, just so they can get noticed more easily, rather than fight for attention in a very crowded platform.

As the Supreme Court pointed out in its recent Amex decision,\(^\text{16}\) some markets with network effects don’t behave all that differently from regular markets. They may, for example, involve one-way indirect network effects, in which case, there’s not a strong feedback loop.

And finally and perhaps most importantly, the empirical evidence doesn’t support the feedback loop theory. Instead, we keep seeing, over and over, the big online incumbents get overthrown by some clever new company. We’ve seen that with social networks, search engines, dating sites, online retailers, transportation services, and so forth.

JAMES COOPER: I would just echo much of what everyone else has said. These questions are very fact specific. Data are non-rivalrous. But we can solve the public good problem if we make it exclusive or proprietary.

I would want to caution against punishing success. Network effects exist because you’ve got a successful product, so you draw lots of people to your platform and the more people, the more data, the better your platform becomes. But once you start saying, “You’ve become so successful and your data are so good that we are going to force you to share it,” then we have to worry about dynamic incentives. So when we think of data as a barrier to entry we have to be careful to balance static and dynamic competition concerns.

The FTC will be exploring some of these interesting and important questions at American University as part of its Competition and Consumer Protection hearings.

BARRY NIGRO: I agree with James that we don’t want to punish success. More specifically, where a firm develops data that’s valuable and gives it a competitive advantage, requiring that firm to then have to share the data because it’s helped the firm succeed would undermine the incentive to invest in new assets to compete for the market. In the short run, it would potentially create more competition within the market, but the dynamic competition that James referenced would be muted or potentially lost if investors taking on risk knew that once they succeeded, they would have to turn around and share the origin of that success with firms that didn’t take on that risk.

I don’t think requiring firms to share their data in that context is a costless exercise. In contrast, if you’re looking at a merger, where a firm is acquiring data that is a critical input to competitors, then we have our usual tools, which we have used for many years, to evaluate that acquisition and assess whether a remedy is required. In that case, it is just another input. I don’t think there’s anything different about it from other types of critical inputs. The antitrust tools that we have are well suited to undertaking that analysis.

AI DENG: We talked about the definition of big data and whether big data is a barrier to entry. Sometimes I feel we also should be clear about what an entry barrier really is. If you look at the economic literature, there are actually a dozen different definitions of what an entry barrier is. It’s

my observation that, in practice, when most of us talk about entry barriers, we have in mind some types of costs, that is, how costly it is to enter or how much time it takes to enter. The two are very often highly correlated. Very often it’s both time-consuming and capital-intensive to enter. But whatever definition we’re using, I think we’ve got to be clear about it. Once we are clear on that, we can then turn to the question of whether big data is a barrier to entry. In my mind, there’s no “yes” or “no” answer to that question.

And in some cases, I agree with Barry and others that standard tools would apply. A leading example in my mind would be, say, in an industry where big data is the product or the output itself. Take the Thomson/Reuters case—that is one where both companies are data vendors. They collect, process, and host economic data and then sell the data to the customers. In such a case, I think, to assess whether the data presents an entry barrier, you can ask standard questions, such as how costly it is to accumulate those data, how much does the human capital cost, how costly are the hardware and software, how much time is that going to take. At least conceptually, I don’t see that we need to take a significantly different approach.

Now, when the big data is used as inputs to improve products and services, the situation tends to be more interesting and can be more subtle. I have a decision tree in my mind when I think about approaching this situation. The first layer of the decision tree would be to look at the four features of big data and ask whether any of those are relevant to the particular industry we’re studying. Let’s say two out of the four are the most relevant features; then we’d ask the standard questions again about those features. For example, if the volume is relevant, then how costly is it to obtain the volume? If velocity is the key feature of that industry, then how costly is it to have the ability to capture real time data?

If the conclusion is that, yes, those features could serve as potential barriers to entry, then we move down to the next layer of the decision tree and ask whether those features are necessary for entry. The analogy I have in mind is to think of big data as ingredients available to a chef. Many of us have watched cooking shows where you are given some random ingredients and your job is to cook a great dish. And different chefs will have different ways to approach a dish. You don’t need to necessarily use exactly the same ingredients to make a great one.

An entrant may enter into the market with a very good idea that could remove or circumvent some of those Vs relevant to the incumbent. For example, they may not need to use as large a data set as incumbents may have to use. There is an active research area in machine learning whose aim is to find ways for machines to learn without using as much data as is typically needed. One example of such an approach in the machine learning field is called transfer learning. People are interested in the idea because they wonder, what if we don’t have this much data? How far can I go with limited data? This is still an active research area in machine learning and AI.

Of course, we should recognize that predicting whether someone could replace the big data with a big idea is typically not easy. And we need to be aware of that limitation.

In any event, I think having a framework such as the one I described can be very helpful when analyzing this question.

DARREN TUCKER: I agree that we need to look at this issue on a market-by-market, case-by-case basis, but we have had a number of cases involving whether data is a barrier to entry. So we can look to for patterns in terms of what the agencies are finding.

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Cases where the agencies have found data to be an entry barrier typically have involved commercial data that was proprietary and difficult to source, and customers often required historical data and a reputation for quality. On the other hand, the agencies have consistently found that personal data, or user data, collected over the internet or through other means do not constitute a barrier to entry. EU and U.S. decisions on point there include Google/DoubleClick and Facebook/WhatsApp.18

Another pattern we can see at this point is that where the agencies have required relief in big data cases is where data is the product, as opposed to an input. Ai made a similar point referencing the Thomson/Reuters case. Other examples include CoreLogic/DataQuick,19 CCC/Mitchell,20 and Dun & Bradstreet/QED.21 In contrast, the U.S. agencies and the European Commission have not required divestitures where data was used as an input.

Even where there have been concerns around data being a particularly important input, the agencies have not required a standalone divestiture of data. A good example is the Nielsen/Arbitron case,22 where the FTC found audience data to be quite important to the end product, yet the divestiture involved the overall measurement platform.

KEVIN CHRISTENSEN: There have been lots of conversations and research discussing whether or not antitrust is the right venue to address privacy concerns. So, I pose that question to you: is antitrust the right venue to address privacy concerns?

JAMES COOPER: I’ll give you an unequivocal “no.” We often talk at the FTC about how the Bureau of Competition and the Bureau of Consumer Protection can work together. But I think this is one place where privacy is probably best left in the domain of Consumer Protection.

I think there are two core problems with moving privacy into the domain of antitrust. And before I continue, let me say that I think the law is clear that courts would not consider privacy directly as a value on a par with consumer welfare in an antitrust analysis. What I’m talking about is smuggling privacy into antitrust as a metric of competition, akin to quality.

So first, antitrust tackles non-price competition, but I think the notion that a reduction in privacy can be analogized to a reduction in quality—or a concomitant increase in price—breaks down under close scrutiny. Suppose an automaker charges the same price for a car but leaves the air conditioner out. It immediately increases its profit from a reduction in quality because its costs are lower. But if a company takes more data from you, they aren’t immediately more profitable. In fact, they’ve invested in the collection and perhaps analysis. The only way to make collecting more data a winning strategy is to monetize it. They do this by using it themselves to offer more tailored products, driving more people to their platform so they can increase ad revenues, or by selling it to others so they can advertise more effectively.

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My point is, at the end of the day, collecting data is about selling something to a consumer. So there's always a benefit tied into the data collection. Now, because tastes and preferences are heterogeneous, some may be privacy sensitive and find increased use of data harmful on net but others may find the bargain—more data for more content and more relevant ads—a net positive. So, unlike quality, which is a vertical dimension, a decision by a firm to take more data is more like positioning oneself in a horizontal space.

As a hypothetical, suppose two firms merge and one has really stringent privacy protections and the other less so. Further suppose that they decide that the new entity will adopt the less privacy-protecting model—the ad-supported application—rather than the paid application.

I would argue that this scenario isn't like a reduction in quality in the same way as if two automakers merged and then decided to exercise market power by maintaining price but reducing the quality of their cars. In the privacy context, because privacy preferences vary, some consumers may prefer that new firm, some may not. Again, it's more like repositioning in a horizontal dimension than in a vertical dimension.

I think the other really big problem of introducing privacy as a dimension of competition is that it introduces a whole range of subjectivity into the analysis. While this will help make sure economists and lawyers continue to make a good living, it will inject more uncertainty into the regulatory system, which is always bad for business. Antitrust analysis can be quite complex, but nonetheless, you have a metric. You have price and output. As you move away from those objectively verifiable metrics, analysis starts to become more subjective and less predictable. Privacy is in the eye of the beholder and so could you imagine that the subjectivity that would go into the Commission, the DOJ, or a court deciding whether a merger that eliminates a privacy-protective firm is harmful to consumers.

Additionally, when you introduce uncertainty and subjectivity, you introduce a lot of dissipative expenditures on rent seeking. As you expand the dimensions over which courts and agency officials can make antitrust enforcement decisions, you'll necessarily draw resources into convincing courts and agency officials to act, or not act, over these dimensions.

BARRY NIGRO: I can imagine circumstances in which privacy is a basis on which firms are competing. In that circumstance, it could be relevant to some extent to the analysis of competitive effects, if privacy was something that consumers valued and it differentiated competition among firms in a significant way. Just like any other point of differentiation, traditional antitrust analysis could take that into account, along with other relevant factors, in evaluating whether the firms are close competitors or not.

I don’t think there’s anything unique about accounting for privacy in that context. I agree with James that privacy for the sake of privacy is better managed using other tools, to the extent that it is a value society wants to promote.

TERRELL McSWEENY: I agree with what Barry's saying. I think the appropriate threshold question for enforcers is whether privacy is a dimension of competition in the markets that are before them. And if it is, then are there quality or innovation effects from a loss of that competition? Are they offset?

It just can’t be assumed that competition on privacy is actually occurring. There must be some evidence of it. The challenge is that we quickly get into a relatively perilous zone for competition enforcers because it's hard to engage in competition analysis based on what you think consumers may want. You can’t create competition and privacy features and services where none
exist, even if you think it would be good to have it—that very quickly leads into the broader privacy policy debate. The debate over whether or not there is an appropriate level of privacy regulation is happening in the U.S. and other parts of the world. We’ve seen implementation of the GDPR in Europe, which is a very strong privacy regulatory framework, and is having a lot of different effects. The complexities within those policy debates really underscores how multifaceted a problem privacy actually is, which is why competition enforcers should be careful about straying too far into the privacy zone.

It’s also important for competition enforcers to be mindful of the tension that may start to exist between privacy regulatory frameworks and competition frameworks. Competition is important to innovation. Innovation and competition both require, to a certain extent, the flow of data in marketplaces. IP privacy regulation results in locking down data, which could result in new barriers of entry forming around data, and the competitive significance of data could change, depending on the policies that are adopted. That might chill innovation.

Some of the most harmful policies, in my view, are data localization policies, which further cabin data in certain countries. And in that space, I think competition enforcers have an advocacy role to play to help policymakers get the balance right between privacy, data protection, and innovation.

DARREN TUCKER: We’ve touched on two discrete issues relating to big data and privacy.

James was principally addressing whether traditional privacy or consumer protection concerns should be incorporated into antitrust analysis. So, for example, if a merger resulted in an accumulation of data, would that by itself be sufficient grounds to block the transaction, even if there was no competitive effect from the data accumulation? I fully agree with James that there are good reasons not to incorporate these privacy considerations into competition analysis. There are different views of what privacy is, and I have no idea how you would balance competition concerns such as price and output with privacy concerns.

If you did incorporate loss of privacy as a potential concern in antitrust enforcement, you’d presumably have to also consider a gain of privacy as a potential efficiency. So if a transaction was otherwise anticompetitive and the merging companies committed to provide greater privacy protections, does that mean that the deal then goes through, even though it’s anticompetitive under a traditional competition viewpoint?

But, thankfully, we don’t have to get to those difficult questions because this is one of those rare areas where the law is crystal clear. It is black letter law that traditional consumer protection concerns, such as privacy, cannot be incorporated into competition analysis. Over 80 years ago, the FTC found that the use of deceptive advertising by the seller of a supposed obesity cure was an unfair method of competition. And the Supreme Court reversed, finding that consumer protection concerns were beyond the FTC’s unfair methods of competition jurisdiction. That decision led the FTC to get its consumer protection authority.

We’ve seen the Supreme Court repeat this point time and time again. In Philadelphia National Bank, Indiana Federation of Dentists, and Professional Engineers, the Supreme Court has

said that the only thing you’re supposed to look at in an antitrust case is the effect on competition. You’re not allowed to look at other economic or social values, as legitimate as they may be in other contexts. You see the same thing in the U.S. Merger Guidelines.

This is not a U.S.-specific view. In the Facebook/WhatsApp case, the European Commission said it didn’t have the authority to consider privacy considerations in the course of a merger review. The European Court of Justice said the same thing in the Asnef-Equifax case. So, there’s a general consensus on this point.

Then there’s the second issue that Barry and Terrell addressed, which is whether privacy is an element of competition that antitrust agencies should consider? That’s a distinct question. And I agree that they should.

Again, we have some Supreme Court guidance. In LinkLine, the Supreme Court said there’s no distinction, as far as antitrust is concerned, between price and non-price effects. Consistent with that, we’ve seen the FTC, DOJ, and EC bring cases on the basis of a reduction in quality, such as Promedica, H&R Block, and the FTC’s Intel and Google investigations.

In theory, as Barry said, you could have concerns about a merger between firms that compete closely on the basis of privacy. But, in practice, this kind of case is going to be extraordinarily rare. There haven’t been any cases along these lines to date despite interest by some regulators in bringing such a case, and even cases alleging quality diminution are relatively rare compared to more traditional effects, such as price and output.

There are a lot of practical difficulties here. For one thing, we don’t have any economic or empirical evidence that increased concentration will lead to a diminution of privacy. More broadly, there’s no correlation between concentration and quality.

It’s interesting that many of the cases where there have been calls to block a merger on the basis of a loss of privacy competition are often the cases that are the least likely to have privacy effects. The classic example is Facebook/WhatsApp. There were consumer and privacy groups urging enforcement under Section 7 on the view that Facebook was likely to reduce WhatApp’s much more robust privacy protections. But in fact, a standard unilateral effects analysis tells us a transaction like that is very unlikely to lead to a reduction in privacy competition because they’re not close competitors on the basis of privacy competition. They’re distant competitors.

A more plausible example of a reduction in privacy competition would be a merger between firms that provide very strong privacy protections. Even in that scenario, antitrust concerns would only arise if the merging parties competed in the same relevant market, repositioning on the basis of privacy was unlikely, and consumers viewed privacy as an important element of competition.

And even for the very rare acquisition where we have legitimate concerns about the loss of competition on the basis of privacy, the anticompetitive effect is probably not going to be less privacy, it’s going to be higher prices or reduced quality. That’s because it’s hard to reduce privacy. There are regulations in the U.S. and now particularly in Europe that make it very difficult for companies to reduce their privacy protections. By contrast, it’s relatively easy to raise prices or spend less money innovating.

29 ProMedica Health Sys., Inc. v. FTC, 749 F.3d 559 (6th Cir. 2014).
JAMES COOPER: Yes, I completely agree that privacy could be a dimension of competition, and in theory could be challenged by the agencies. I agree with that, but I still think looking at privacy as a dimension of competition raises a serious subjectivity problem. In the case of two firms that are competing closely on privacy, how would you determine that they’re competing closely on privacy? And let’s say that they come together and now we just have one firm that’s really privacy-sensitive as opposed to two, what does that really mean for consumers? What if the combined firm stops being as privacy-protective? How do you measure market share? How do you measure the extent to which privacy in a marketplace has been diminished?

So, again, in the realm of theory, you can certainly imagine a scenario where we have evidence that two firms were competing on privacy, and that it was important to consumer decision-making. But in practice, I think you will end up with a great deal of subjectivity, which to me is really a first order concern.

BARRY NIGRO: Both the FTC and the Department of Justice have to go to court and explain to a judge why a transaction will reduce competition. If there isn’t relatively strong evidence in the documents and the testimony that it’s an issue, you’re likely not going to see a case.

The question is whether there’s evidence that it’s a meaningful dimension of competition between the firms, whether, as a result, they’re closer competitors than the other firms in the market, and the competitive significance of it. I don’t think there are likely to be many cases like that, but who knows? It’s like any other qualitative factor that affects whether firms are close competitors.

AI DENG: It is often raised that one challenge in thinking about privacy as a type of quality is that there’s a lot of heterogeneity, i.e., different people value their privacy differently, and it’s really hard to put a number on it, unlike a price.

For example, I use two social media platforms, and one has a very stringent privacy restriction. I don’t see any posts or replies by anybody who I’m not connected with. I also use Facebook, where I can see posts by people I don’t know. Do I value the privacy offered by the other platform? On the margin, maybe I do. But by how much? I have not figured it out. I think that speaks to this type of heterogeneity and challenge. I know some had proposed the idea that we might just need to better educate consumers, give them more information about what privacy means, what the companies are using the information for, just so consumers know the value of the information they’re sharing. But some have also argued that this is not going to be that useful.

I am sure there will be a lot more discussions and research to come. But when we think about whether privacy is a competition issue, I believe it is relevant to understand how consumers value it.

DARREN TUCKER: I agree that there is a wide range of views of privacy among consumers. And some consumers view privacy, at least in certain contexts, as a negative. There are over 10 million people that have a public Facebook account, for example, and there are lots of other social networking services that are designed to broadcast personal information as widely as possible.

In the context of a merger review or other antitrust proceeding looking at the importance of privacy competition to consumers, it may be challenging for authorities to accurately gauge consumers’ privacy preferences. There is often a wide differential between what consumers will say in a survey, for example, about their privacy preferences versus their actual behavior. So, the same consumer who will say that he feels strongly about protecting his privacy and doesn’t want firms
to collect his personal information, will then turn around and fill out a card to enter a contest, pro-
viding lots of personal information for a prize effectively worth a few cents.

And so it's important to make sure you have good data in this context, and looking at revealed preferences is generally going to be superior to survey-based approaches.

TERRELL McSWEENY: We’re not going to solve the privacy policy debate in this discussion. You’re making a relevant point, but I think the privacy policy debate is far, far broader and more multi-faceted, which is why the competition tool is not necessarily the right tool to address it. As we discussed, enforcers quickly get into that gray area that we’ve been navigating, and it’s confusing and hard to figure out how to achieve the right balance.

That said, I think there is also a case to be made that there’s a bit of a market failure when it comes to privacy data policy because of the well-documented information asymmetries that exist in the marketplace. Most people don’t have a great sense of what the deal is when they’re exchanging their data. They’re getting a better sense, and we’re seeing it result in people starting to have a different relationship with technology.

I think we all ought to be very concerned about an erosion in trust in technology because it could affect adoption. For innovation to flourish and for competition to flourish, consumers need to have confidence in technology. So these are important areas for discussion, debate, and engagement.

KEVIN YINGLING: That’s a good place to end. Thank you all for spending your morning with us discussing big data. It’s been a great conversation and we really appreciate it.
Automated Pricing Algorithms and Collusion: A Brave New World or Old Wine in New Bottles?

Sheng Li and Claire Chunying Xie

Automated algorithms, which may incorporate analysis from machine learning artificial intelligence (AI), are increasingly used by firms to optimize their pricing decisions. For example, algorithms used by ride-sharing companies such as Uber and Lyft adjust prices of car rides in real time to balance the supply of available drivers and the demand for rides. Dynamic pricing algorithms are also expanding into brick-and-mortar stores, with physical stores like Kohl’s and Nebraska Furniture Mart adopting electronic price tags to match the latest offers from online competitors and with firms such as McKinsey and Eversight providing software that enables AI-driven algorithmic pricing at brick-and-mortar retail chains.1 The use of such automated pricing algorithms in conjunction with big data has the potential to provide significant benefits to consumers by enabling suppliers to become more efficient and swift in responding to market demands.

However, some regulators and industry participants have raised concerns that the adoption of automated pricing algorithms may increase the likelihood of tacit collusion, perhaps even without direction from human decision makers. From an economics perspective, the question can be framed this way: whether (1) automated pricing algorithms represent a brave new world that requires new tools and a paradigm shift in the way we think about collusion, or (2) those antitrust concerns can be appropriately analyzed using principles built up over decades of research into the economics of collusion.

This article examines the features of automated algorithmic pricing that spark concerns about tacit collusion and considers what economic theory can tell us about how increased adoption of automated algorithmic pricing may influence firms’ incentives to collude. We find that possible collusion in algorithmic pricing can and should be analyzed using principles of economics that have been refined over decades. Moreover, economic theory teaches that, while the use of automated pricing algorithms may reduce some barriers to collusion, it may also intensify other factors that raise barriers to collusion. Assessing the competitive effects of algorithmic pricing requires careful economic analysis that considers the totality of the market-specific conditions in each case.

A Brave New World of Automated Collusion?

Some academics, industry participants, and regulators have suggested that an extensive use of automated pricing algorithms may increase the likelihood of collusion. For example, Ariel Ezrachi and Maurice Stucke warn of a future where “as competitors’ prices shift online, their algorithms

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can assess and adjust prices . . . within milliseconds . . . swiftly match[ing] a rival’s discount, thus eliminating its incentive to discount in the first place.”

A 2017 report from the Organization for Economic Co-operation and Development (OECD) expressed concerns that the use of algorithmic pricing may result in “high price transparency and high-frequency trading that allows companies to react fast and aggressively [which] could make collusive strategies stable” and that “algorithms might enable firms to achieve the same outcomes of traditional hard core cartels through tacit collusion.”

These concerns were echoed in a recent article co-authored by then-FTC Commissioner Terrell McSweeney, which discusses a “possibility . . . that algorithms may facilitate tacit collusion between competitors” and cites a finding by Bruno Salcedo “that under certain conditions, tacit collusion between firms employing pricing algorithms is . . . inevitable.”

Participants at the recent 2018 FTC hearings on “Competition and Consumer Protection in the 21st Century” discussed similar concerns regarding the likelihood of such algorithmic collusion.

The concerns raised over potential collusion using pricing algorithms can be grouped into three scenarios: (1) the use of automated algorithms to implement explicit collusive pricing agreements between competitors; (2) “hub-and-spoke” scenarios where competitors (spokes) use a common third-party pricing algorithm (hub), which may lead to coordinated pricing; and (3) unilateral use of self-learning autonomous pricing algorithms by competitors that may nonetheless lead to supra-competitive prices through conscious parallelism or tacit collusion. The economic analyses presented in this article apply to the economic principles and market forces that affect the likelihood of collusion arising from all three scenarios.

The first and second scenarios described above both require explicit agreements on the part of human decision makers—these are essentially the smoke-filled room agreements of the digital era. The first online marketplace antitrust prosecution by the DOJ is such an example of an agreement implemented using computer algorithms. However, it has always been possible for competitors to coordinate—either directly, or through human third-party “hub” pricing schemes, such as a common third-party consulting agency, without the use of any automated algorithms. In the words of former FTC Commissioner Maureen Olhausen, “If it isn’t ok for a guy named Bob to do it, then it probably isn’t ok for an algorithm to do it either.”

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The economics of these types of collusion scenarios do not change when algorithms are involved, and as such, the fundamental economic problem of coordination applies to potential collusive schemes, whether it be through automated pricing algorithms or human agreement. These scenarios of collusion still fundamentally depend on human agreement.

The third scenario of potential collusion envisions situations in which, even without explicit agreements among competitors, unilateral use of automated pricing algorithms by competitors may lead to supracompetitive prices through conscious parallelism or tacit collusion. As a preliminary matter, as acknowledged by Ezrachi and Stucke, “[a]lgorithmic tacit collusion will not affect every (or even most) markets.” In their discussions of algorithmic tacit collusion scenarios, Ezrachi and Stucke focus on concentrated markets where credible deterrent mechanisms exist for enforcing collusion and barriers to entry are high—market settings that have been identified in classical economic studies to have elevated risks of collusion.

Within the context of such market settings, the discussion often centers around two features of algorithmic pricing: (1) greater transparency of prices as sellers post their prices online and more market data becomes accessible, which purportedly makes it easier for collusive firms to detect those that cheat and undercut the collusive price; and (2) the ability to rapidly react to competitors’ pricing changes, which purportedly enables collusive firms to rapidly punish cheating firms that undercut the collusive price (by matching or further undercutting the prices of the cheating firm). These two features correspond to factors that are well understood within the economic literature to affect the sustainability of collusion in general—information availability and frequency of interaction between competitors. As such, how changes in these factors would influence incentives to collude and the sustainability of collusive arrangements are well within the scope of economic models of competition developed over the decades. Just as the increased calculation speeds by computers do not change the fundamental laws of mathematics, the increased velocity of decision making by automated algorithms does not change the fundamental forces of competition.

Tacit collusion between AI pricing algorithms remains within the realm of hypothetical predictions. There has been no empirical evidence demonstrating collusion between AI algorithms in real-world markets—a fact the Canadian Competition Bureau noted when it stated that “suggesting a fundamental shift in cartel law enforcement” to address such hypothetical concerns would be “premature.” Maureen Ohlhausen similarly stated that “[f]rom an antitrust perspective, the expanding use of algorithms raises familiar issues that are well within the existing canon” and that, while the “enforcement agencies should remain vigilant” about pricing algorithms, she is “not yet afraid of the things that go beep in the night.”

The absence of evidence from empirical studies on real world market settings does not appear to be driven by a lack of interest from economists. On the contrary, the economic implications of

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10 See, e.g., id. at 3–4.
12 Ohlhausen 2017 Speech, supra note 8, at 11.
AI are the subject of intense interest from professional economists, as can be seen through the wide range of research presented at the annual “Economics of AI” conference hosted by the National Bureau of Economic Research, including studies on the effects of AI on competition between firms. However, given the absence of empirical evidence from real-world market settings, the research on tacit collusion between AI pricing algorithms remains a theoretical inquiry with no demonstrated real-world evidence.

Economic models are capable of assessing the effects of automated algorithms on incentives to collude, whether tacitly or explicitly. This is because automated algorithmic pricing does not change the fundamental economic principles that govern competition and incentives to collude. The effects of automated algorithmic pricing likely will differ case by case, based on the specific algorithms used and the specific market conditions. To properly assess such effects, we must apply economic principles to the facts of each case and holistically examine the ways in which automated pricing algorithms may change how firms interact and their incentives to collude.

As we discuss below, increases in information availability and frequency of interaction between competitors are not the only ways in which automated pricing algorithms can change economic incentives to collude. On the contrary, the same technology that brings about increases in information availability and frequency of interaction between competitors may also engender factors that hinder collusion.

Rational Decision Makers Are Not New in Economics

While automated algorithms and AI, hailed by some as a key driver of the “Fourth Industrial Revolution,” are undeniably transforming the economy, the economic principles that underlie demand, supply, and competition have not changed. Decisions by competitors to collude, whether through explicit smoke-filled-room agreements or through interactions of automated algorithms, will continue to be driven by the economic incentives facing the decision makers.

Classical economic models of competition consider decision making by rational market participants. Strategic interactions and price competition between those market participants can be thought of as “games” defined by what information (e.g., competitors’ prices and pricing histories) each firm has access to, the choice of actions (e.g., pricing) available to each firm, and profits and sales each firm would earn given their pricing choices. Given these factors, a rational agent chooses the strategy that maximizes its profits.

This objective to maximize profits is the same whether prices are set by humans or automated pricing algorithms. Some commentators have opined that classical economic models may not be applicable for assessing algorithmic pricing based on arguments in the vein of “[a]ll of the economic models are based on human incentives and what we think humans rationally will do. It’s

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16 This is the game-theory framework for analyzing strategic interactions, first developed by Nobel Laureate John Nash. Within the game-theory framework, games of strategic interaction are defined by the list of players participating in the game, the information and actions available to each player at each decision point, and the payoffs for each outcome of the game. See, e.g., Martin J. Osborne, An Introduction to Game Theory 13–14 (2004).
entirely possible that not all of that learning is necessarily applicable in some of these markets." 17

However, such arguments are based on misconceptions of what is rational decision making and/or the underlying assumptions of classical economic models. Decision making, as the automated pricing algorithms are programmed to carry out, is no different from the type of decision making that is governed by mathematical logic with the goal of maximizing profits for the firm. These are exactly the scenarios modeled in classical economics.

Given the firms’ chosen pricing strategies, profits are driven by demand and costs facing each firm—market forces that govern both human and algorithmic pricing competition. Therefore, automated pricing algorithms do not change any of the ground rules of price competition between firms. As discussed above, commentators have suggested that automated pricing algorithms may change the information available to decision makers in these games and the speed of the game 18 because some automated algorithms can react to market developments in a matter of milliseconds, increasing the frequency of interactions between firms. In addition, commentators have argued that the same technology that gives rise to the use of automated pricing algorithms can increase the amount of information each firm observes and relies upon in its pricing decisions, reducing information asymmetry across firms. 19

There is an extensive economics literature that examines strategic pricing interactions between rational agents with varying degrees of information asymmetry and interaction time. 20 Below, we discuss what we can learn from the economics literature about how these changes brought about by automated pricing algorithms may influence incentives for collusion.


Classic economic theory of collusion teaches that firms need to resolve a series of problems to sustain collusion. First, firms need to reach a collusive arrangement. That is, each firm needs to find it in its unilateral best interest to adopt the cooperative (i.e., collusive) strategy rather than a competitive one. This problem of finding a collusive strategy that all firms are willing to adopt is common to overt and tacit collusion. Second, for collusion to be sustained, firms need to find it in their unilateral best interest to follow through with the collusive strategy without deviation. That is, the economic benefit from sticking with the collusive strategy needs to exceed the economic benefit from unilaterally deviating from it. A collusive arrangement that raises the industry prices above competitive levels engenders economic incentives for individual firms to undercut their competitors’ prices to capture a larger share of the market (i.e., to cheat on the collusive arrangement). Mechanisms to detect and punish such behavior are necessary to discourage cheating on the collusive arrangement and sustain collusion. Below, we discuss these and other economic fac-

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19 See sources cited, supra note 18.

20 The classic prisoner’s dilemma assumes that there is no information asymmetry between the firms—both firms know the profit that each firm would make under different market outcomes. Edward Green and Robert Porter developed an economic model in which a firm’s output is private information. Because firms do not observe others’ output level, they cannot distinguish what might have caused a decline in sales—a deviation by another firm from the corporative strategy (i.e., an expansion in output) or a low demand shock. Edward J. Green & Robert H. Porter, *Noncooperative Collusion Under Imperfect Price Information*, 52 ECONOMETRICA 89–90 (1984).
tors that can hinder or facilitate collusion and whether those factors change with the use of automated pricing algorithms.  

**Ability to Reach a Collusive Arrangement.** Economic incentives to collude exist when the total economic profits from collusion (i.e., when firms make joint decisions to maximize industry profit) exceed the total economic profits from competition. Consider two markets that are identical except that one market has only one supplier (a monopoly) and the other has two (a duopoly). It is well established in economics that the profit made by the monopolist exceeds the combined profits of the two firms in the duopoly. Those two firms therefore have an economic incentive to act jointly to behave like a monopoly and split the monopoly profit.

Having economic incentives to collude does not necessarily engender a collusive outcome. To sustain collusion, the colluding firms must find a way to split the gains from collusion such that all participants in the collusive scheme are made better off. Otherwise, firms would find it in their unilateral best interests to adopt the competitive strategy rather than to cooperate in the collusive scheme. Therefore, a mechanism to split the gains from collusion is necessary for sustaining collusion, whether it be overt or tacit. The use of automated pricing algorithms does not eliminate the need for such profit-splitting mechanisms to reach a collusive arrangement.

Several market conditions can affect the likelihood of finding a way to split the gains from collusion. In a simplified example in which all firms are identical (i.e., firms make the same product and face the same cost), there may be relatively straightforward ways to divide the gains from collusion. For example, some market allocation arrangements may ensure firms can equally distribute gains from collusion.

However, finding a way to split the gain from collusion may be harder when firms are asymmetric. Firms can differ in many aspects. For example, asymmetry in costs can arise when firms have different levels of productivity. A well-managed firm may be more productive, and thereby more efficient, than its competitors.

Cost asymmetry may complicate the allocation of gains from collusion. Take, for example, a scenario in which there are two firms, one with a higher cost of production than the other firm. A collusive scheme may be for the firm with the lower cost to supply the entire market and then share its profit with the firm with the higher cost. Reaching an agreement on how the gains from such an arrangement should be split may involve side payments from one firm to the other. Setting aside the legal implications of such payments, a series of other economic problems need to be resolved before both firms would agree to such a collusive arrangement. For example, how would such a transfer take place? How will the firms solve the commitment issue—i.e., can the firm with the higher cost be certain that the firm that supplies the entire market will share the profit rather than keep the profit to itself?

The use of automated pricing algorithms does not alleviate coordination issues that must be resolved to implement either overt or tacit collusion. For example, it remains an open question the extent to which, if at all, the use of automated algorithms can solve the allocation issue in the presence of cost asymmetries. In the first instance, the use of automated pricing algorithms is unlikely to resolve cost asymmetries across firms. Second, economic literature provides no predictions

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21 The discussion below is not meant to provide an exhaustive list of such economic factors. For a more detailed discussion of the economic theories of collusion, see, e.g., Alexis Jacquemin & Margaret E. Slade, Cartels, Collusion, and Horizontal Merger, 1 Handbook of Industrial Organization 417–23 (Richard Schmalensee & Robert Willig eds., 1989).

22 Id. at 418.
on how automated algorithms can facilitate finding ways to divide gains from collusion in cases when no such agreements are reached by humans.

**Incentives to Cheat.** As firms enter into a collusive arrangement, they have incentives to cheat by deviating from the collusive arrangement and undercutting competitors to obtain larger market shares. Such unilateral deviations from the collusive strategy can result in substantial increases in profit made by that firm while the other firms continue to implement the collusive strategy.

Economics teaches that a key step to assess the sustainability of collusion is to examine the market conditions that can affect firms’ incentives to cheat on the collusive prices and/or quantities. A firm’s incentive to cheat depends on how much more in sales it can obtain by offering a lower price—a concept known as demand elasticity. The higher the demand elasticity, the more sales the firm can obtain with a reduction in price, and hence increasing the incentive to cheat.

A firm’s cost structure can also affect its incentive to cheat and undercut collusive prices. For a firm with high fixed costs, restricting output as part of a collusive arrangement may not only result in excess production capacity but also limit the firm’s ability to recover its fixed cost. Therefore, compared to firms with low fixed costs, firms with high fixed costs may have more economic incentives to cheat on collusive agreements by expanding output.

It remains an open question whether and how the use of automated pricing algorithms affects the demand and cost conditions mentioned above. For example, the rise of online retail and automated comparison-shopping services such as Google Shopping and Kayak may make consumers more price sensitive, thereby increasing the demand elasticities and economic incentives for firms to gain sales by undercutting collusive prices. On the other hand, the rise of e-commerce may also increase the level of product differentiation, making the products more tailored to specific groups of consumers, resulting in more inelastic demand for those products.

**Mechanisms to Deter Cheating on Collusive Arrangements.** Because firms have incentives to cheat on collusive arrangements, mechanisms to deter cheating must exist to sustain collusion. Such deterrence can take various forms, but the basic intuition is the same—the prospect that cheating would be met with punishment severe enough to make the costs of cheating outweigh its benefits.

The effectiveness of a deterrence mechanism depends on several factors: (1) whether cheating can be easily detected; (2) the severity of the expected punishment; and (3) the credibility of the prospect of punishment. Below we discuss market conditions that can affect each of those factors.

Whether cheating can be easily detected by co-conspirators depends on the existence and extent of information asymmetry. In a world in which all information is observed by all firms, detection is straightforward—cheating can be observed as demand, price, cost, and even a firm’s pricing strategy are public information in a world with full information. However, firms often have private information on pricing and costs. In the presence of private information, detection becomes less straightforward.

While, as suggested by some commentators, the use of automated pricing algorithms may alleviate information asymmetry, it may also contribute to information asymmetry, which, as discussed above, hinders collusion. Companies may develop their own automated pricing algorithms or use different suppliers to manage their automated pricing algorithms. It therefore becomes

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unclear what information each algorithm would consider when making pricing decisions. Put differently, when one algorithm considers a set of factors and a second algorithm does not, it is as if those factors are private information to the first algorithm. In this way, the use of automated pricing algorithms therefore may increase information asymmetry.24

A deterrence mechanism’s effectiveness also depends on the time needed to implement punishment after cheating is detected. To understand this, consider a scenario in which, when a firm cheats on the collusive price, all other firms in the collusive cartel will punish the cheating firm by pricing their competing products at low prices going forward. Hence, the cheating firm would make higher profits while the cheating remains undetected, but after cheating is detected, it will make lower profits than if it had not cheated. This is because competition from the other firms’ low prices would reduce the cheating firm’s profits. The punishment is therefore the decline in future profits. The firm would cheat only if the temporary increase in profits from cheating is greater than the decline in future profits. The longer it takes to detect cheating, the larger the gain from cheating.

The frequency with which competitors can react to each other’s price changes is a factor that affects the time lags between cheating, detection, and punishment. As interactions become more frequent, the time lags between interactions shorten and the possibility of a punishment becomes more immediate, increasing the deterrence effect of punishment threats. All else being equal, if the time lags between cheating, detection, and punishment are reduced, the costs of cheating on a collusive agreement would increase.

Commentators have raised the concern that automated algorithms would decrease these time lags and make collusion more likely. However, the rapid reaction speeds enabled by automated pricing algorithms and online retail platforms may be somewhat of a double-edged sword for would-be collusive firms. While the increased reaction speeds may allow for faster detection and punishment of cheating firms, online retail platforms and algorithmic pricing may also change the market landscape in other ways that make collusion more difficult. For example, online retail platforms such as Amazon and Alibaba enable sellers from around the globe to compete for local sales,25 and the rapid-reaction pricing may sharpen competition and spark price wars that would make collusion difficult.26

Detection and reaction time lags are not the only factors that influence the ability of conspiring firms to enforce collusion. The severity of a punishment may be bound by other factors such as capacity constraints. In industries where increasing production capacity in the short term is difficult, conspiring firms may not be able to expand output sufficiently to deter cheating. The use of rapid-reaction automated pricing algorithms would not make collusion any easier in such circumstances.

**Entry.** Another important factor is the threat of entry by additional competitors when incumbent firms collude. As collusion raises price, it naturally attracts new firms to enter the market. Economics teaches us that in the absence of entry barriers, new competitors would continue to enter the market until the excess profit from collusion dissipates through increased competition. When entry barriers are present, it would be economically rational for new competitors to enter as long

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as profits under the collusion-inflated prices exceed the costs of entry. Therefore, entry by competitors would still restrain the ability of incumbents to raise prices through collusion. The growth of online commerce that goes hand-in-hand with adoption of automated pricing algorithms has led to the creation of online marketplace platforms such as Amazon, eBay, and Google Shopping that arguably lowers the barriers to entry for online retail. To the extent that such platforms are lowering the barriers to entry, they are sharpening the threats of competitive entry, which raises the difficulty of sustaining collusion.

**Conclusion**

The economics behind antitrust cases involving collusion, by its nature, is complex and nuanced. Adding automated pricing algorithms to the mix only increases the complexity. As such, it should be no surprise that there is no simple “yes” or “no” answer to the question of whether the use of automated algorithms will increase the likelihood of collusion. However, while the strategic games of competitive pricing may now be played at a faster tempo by automated algorithms, the fundamental rules of the game—governed by classical economic principles of supply, demand, and profit maximization—remain the same. Collusion, whether between human conspirators or among automated pricing algorithms, can and should be analyzed using the economic theory that has been honed and refined over the decades.

Applying economic theory to the impact of automated pricing algorithms on market conditions, we find that while the use of automated pricing algorithms may reduce some factors that hinder collusion (e.g., the time it would take for colluding firms to react to cheating), it may also intensify other factors that hinder collusion (e.g., reducing marginal costs and increasing incentives to undercut collusive prices). Assessment of collusion and its economic effects has always required, and always will require careful economic analysis that is informed by rigorous economic theory and considers the totality of the market-specific conditions in each case.
Navigating Economic Analysis in a World of Big Data

Allan Shampine, Loren Poulsen, and Michael Sabor

The availability of more and larger data sets has enabled consultants to develop more complex analyses that may offer greater precision in the estimation of the antitrust effects of alleged mergers or anticompetitive practices (e.g., price fixing). New types of projects are being undertaken, as are more complex versions of the type of analyses offered in prior matters.

This is an evolving area, and even counsel who have often worked with consultants on empirical projects may be surprised that those which had become seemingly routine in the past are now proving slower and harder to adjust to changing circumstances—due to both the increase in big data availability and the more complex analytic tools developed to process those data. While there is no bright line for what constitutes “big data,” if you are dealing with multiple terabytes of data then the analysis is likely to have moved past the common practice of 20 years ago.

This article discusses some practical considerations practitioners may encounter as a result of larger and more diverse data sets and provides an example of taking an analysis from initial stages to final work product, focusing on how changes in big data may raise new concerns at various stages. Practitioners should be aware of both the advantages and potential pitfalls of relying on big data.

At a big picture level, the questions being asked are not new. But there are now new ways to try to answer those questions, which can be seen in three types of commonly used analyses: (1) cross-sectional analysis, (2) longitudinal studies, and (3) demand modeling.

Using Common Analyses and Modeling with Big Data Sets

In the context of antitrust, cross-sectional analysis refers to studying differences in prices and demand patterns between different geographic areas, taking advantage of differences in competitors’ presence or relative size in different regions, or the presence or absence of particular concerns (e.g., discrimination across different customer groupings). These sorts of analyses are common in antitrust practice and may be relevant for examining price fixing, information sharing, mergers, or market definition. Here big data does not qualitatively change the sorts of questions that might be asked, or even at a general level how one might ask them, but it does allow levels of granularity that were unimaginable a few decades ago. That is, big data can help us, for example, by looking at very specific cross-sections of customers to determine if there are different behaviors across different classes of customers. Rather than looking at the “representative consumer” in a demand analysis, we can ask if these same patterns persist in households with different levels of income, education, native language spoken, or ethnic background. This allows for a more flexible functional form of demand (in technical terms, essentially an unspecified, non-parametric demand function) that can then be used to ask the counterfactual questions that are typical of those used in antitrust.

Big data can also be used in a cross-sectional analysis to estimate possible competitive effects directly. For example, how does the presence or absence of a competitor or particular policy
change impact consumers? Can differences in consumer prices or behaviors be observed between different areas with different competitive conditions? For example, it is becoming more common for retailers to engage in controlled experiments with pricing or policy changes, applying those changes to only some customers, or only for a short period of time. Such experiments are not only more common than in the past, but are performed at much larger scales, possibly affecting millions of consumers, and thus yielding far more data than in the past. These experiments may provide indirect evidence of competitive effects, or, at the least, more evidence on the form of consumer demand.

Longitudinal studies look at differences across time addressing the same kinds of questions as above but adding a time dimension to the analysis. Again, these are commonly used in antitrust analysis, particularly when assessing the existence of price fixing and evaluating the competitive risk from mergers. With the cost of data storage decreasing, it is more often the case that the client may now have much more historical data than previously available. But in addition to the standard questions, longitudinal big data also allows us to ask more interesting questions related to changes in market structure over time. For instance, perhaps all markets today have the same competitors but those competitors historically have expanded from different regions. Time series analysis can allow us to understand how competition has evolved over time region by region, state by state, or even city by city in some cases. Here, we can now do analyses that were not previously possible because the data did not exist. Big data has been around long enough that it is becoming more likely that there will be rich data sets available far enough into the past that they can address these sorts of questions.

Demand modeling is an example of a specific type of analysis, mentioned above, that can be approached either with cross-sectional or longitudinal data. In practice, demand modeling has changed considerably in recent decades. Indeed, large, sophisticated companies with many consumers may perform a series of experiments holding constant demographics and changing prices or product attributes to understand how it changes demand for their products and where consumers go (in terms of locations or a different product space) in the face of a price increase or quality decrease. Historically, firms like these have conducted surveys or small-scale experiments and then built a formal model of demand using the insights of those initial efforts with the goal of predicting how consumers will react to various product and price changes or sales approaches.

With the availability of big data, firms may approach the problem of estimating consumer price sensitivity rather differently with less theoretical demand modeling, allowing for more flexible functional forms and “letting the data do the talking.” This difference has important implications as the investigation proceeds while using big data. Specifically, there can be conceptual differences between client firms and economists in how to approach these problems. As noted above, under the traditional approach, a firm might have a theory on what drives consumer demand and build a model based on that theory. The firm might then use data to try and calibrate the model and make predictions. With big data now available, a firm might work in the other direction—start by measuring the relationships between all of the available variables and consumer behavior and then write down a predictive model based on those observed relationships without any attempt to motivate the underlying economic relationships between the variable of interest and its covariates. Given enough data and computing power, such predictions may be very useful to a business. However, an economist may find it challenging to fit a pre-existing ad hoc predictive model of this sort into a traditional antitrust analysis. Here, the economist may either construct a new demand model or try to observe competitive impacts directly.1

1 Of course, the economist may have to explain to the court or the antitrust authorities how and why the models differ.
The key to all three of these analyses (cross-sectional, longitudinal, and demand modeling) is having access to a rich set of covariates, such as demographics, competitive pricing, and changes in structure of competition or product attributes. Big data can be helpful here but can also present challenges. For example, there are some peculiar tensions with big data when it comes to statistical significance. As an illustration, big data may contain an enormous amount of granularity with respect to all sorts of consumer characteristics, so much so that any particular slice of the data may end up being quite small. That is, an analyst might have access to years’ worth of transactions data for millions of consumers, but there might be so much detail about the consumers that the analysis is being done based on small income slices at the census block level, which may result in any given slice having only a handful of consumers in it. Thus, data that is big in the sense of having many, many fields for a particular observation can lead to extremely small relevant groups, while data that is big in the sense of having many different people or firms represented can lead to extremely big groups, which can pose a different set of problems, such as improper aggregation (which could mask the effects of relevant characteristics).

The lesson is that big data can give us the freedom to ask more detailed questions and tease out specific nuances of consumer behavior but can also result in losing sight of the forest because of the trees. Just because we can look at extremely granular data does not mean we necessarily should. The granularity may or may not shed additional light on the question of interest, and may obscure it, but it may also reveal subtleties that aggregation obscured. Another challenge of big data is that conventional tools may not have been designed to handle such large data sets, which can pose practical problems (e.g., will a particular software package be able to process the millions of observations at all). But there also are significant theoretical problems: if the package does run, should the interpretation of the results change? A great deal of econometric work is focused on drawing inferences and making predictions about a population based on studying a sample. However, with big data we may not have to settle for a sample—we may literally be able to study the entire relevant population, or a very large portion of it. That is, traditionally, regression analysis (and statistics in general) have been used to infer central tendencies of various populations from samples of that population. Because they were only small samples, questions about the reliability of the estimate (e.g., confidence intervals and statistical significance) played a central role in the analysis. The legal framework recognizes the analytic importance of those questions, and counsel will often expect any estimates to be accompanied by statistical measures of the reliability of those estimates.

The challenge with a small data set is that any model may be imprecisely estimated because, by definition, there are not enough data to generate very precise estimates. With big data, that particular limitation may disappear, but that does not mean that a model with very small standard errors is necessarily reliable. Rather, the focus shifts to other sources of error. That is, with billions of observations, any model may be very precisely estimated in the sense of the coefficients having very small standard errors, but the same may be true for any number of possible model spec-

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3 It may also be the case that the interpretation of some particular statistical tests may change. For example, some tests may be motivated based on small sample properties, and those properties may be different in a big data world. In the extreme, the analyst might not have a “sample” at all, but might have data on the entire population. However, the more relevant issue from the practitioners’ perspective in the legal context is likely to be a shift in how much attention is paid to different potential sources of error.
ifications. Debates over model specification may therefore become more critical than in the pre-big data universe, while debates over statistical significance become less so. Similarly, other sources of error (e.g., measurement error, bias, model robustness, etc.) are also likely to become more important topics. The presentation and framing of results in terms of statistical significance and the choice of estimated models may therefore be different than in the past. This is very much an evolving discussion amongst practitioners and one that needs to be closely watched.4

Anatomy of a Big Data Engagement

The discussion above is general. But it is also important to consider the specific ways in which a big data engagement, from data acquisition to data processing and then to final output, differ from a more traditional engagement (i.e., one with more limited data). The remainder of this article discusses a hypothetical big data engagement, and describes how differences from a traditional engagement can affect the practicality of using big data to assess antitrust questions.

A first step is to determine whether the engagement involves big data. Here, the analyst will discuss with the client the scope of the data available: number of tables, number of observations per table, number of columns per table, number of string versus numeric columns, and, of course, the total size of the data. As noted earlier, there is no bright line for what constitutes “big data,” but if the answer to the “data size” question is “multiple terabytes,” then you are well beyond the data sizes of even five years ago.

The data collection process, requiring as it does close coordination between the analysts and clients, has always posed challenges, but those challenges can be substantially different with big data. The difference can be thought of as between a trickle of water and a fire hose. Historically, the analyst may have had to make due with a trickle of data, making the best use possible of limited data. Every drop was precious. With big data, the analyst may be confronted with a fire hose of data, much of which may ultimately be irrelevant. Determining and extracting the relevant parts (which are still likely to be extremely large) can be a substantial challenge. Thus, finding the “correct” database or data files amongst the client’s collection is always an issue, but the particular challenges may change from trying to find any relevant data at all to paring down the many possible data analyses to a manageable subset of the data.

Once the analyst and client have reached agreement on the data to be transferred, the data export process itself will depend greatly on whether big data are involved. There are often trade-offs between ease of export and ease of use by the analyst. For example, an Oracle database can be easily exported using Oracle’s proprietary backup facility, but this is typically a costly and inconvenient method for the analyst. Alternatively, the client can create tables that include the relevant data by writing to “flat text files,” which are easy to read and use in many other software packages but require more effort on the part of the client to assemble the relevant data set.

Many export methods allow users to break up and compress a data set, e.g., to export the data set to many files versus a single large file, and some allow for specific data size limitations imposed by the analyst. For example, the client may choose to break the output up into many files where the maximum size is specified, so that the client can be assured the files will fit over some transport medium, such as an e-mail attachment limit or a high-capacity thumb drive. This consideration can impact the difficulty of transporting and the ingesting of data and will be a function of both the size of data being sent and the facilities of the analyst.

4 See Athey et al., supra note 2.
Practitioners are generally familiar with compression algorithms such as “zip” files used for data “export” to the consultant, and there are many compression algorithms, many of which will also allow for the compressed data to be broken up into multiple pieces for transport. For large data files, however, this process of compression and decompression, dividing and recombining, can be time consuming and may provide less assistance in transport than might be expected. That is, compressing a few hundred megabytes of data into three ten-megabyte files that can be e-mailed may be very useful. Compressing a few hundred terabytes of data into thousands of ten megabyte files will be time consuming and will still not make e-mail practical for transmission. We discuss the transport issues further below.

Privacy issues are also common with big data and can complicate production and transport because encryption is more challenging and time consuming than in the past, simply because of the volumes involved. The encryption may occur on different “data size” levels, such as encrypting individual files or full disk encryption. Furthermore, both compression and encryption are likely to be used together. In conjunction, and for large amounts of data, compression/encryption and decompression/decryption can be time consuming, particularly if the data are also being broken up into smaller files. Errors and incompatibilities can also arise, which will be time consuming to sort out. We have all experienced problems with zip file productions, for example, and know how the back-and-forth to resolve those problems can take days. Now imagine doing that with multi-terabyte files that are being transferred back and forth by hand-delivered hard drives and that take a day to decompress/decrypt even when everything works correctly. The time required to resolve these types of transfer issues could be substantial, even before any actual antitrust analysis begins.

The physical transport of big data poses challenges as well. E-mail is typically not a realistic option for big data. But there are other common methods. First, an electronic transfer. A secure FTP site with significant bandwidth capabilities might be used. The “significant bandwidth” condition is critical. Both the FTP host and recipient need to have significant bandwidth available, given the large size of the data. As a result, most client and analyst FTPs in everyday use will not be appropriate.

Second, hard drives or thumb drives can be used. There are practical issues involving making multiple copies and arranging for physical delivery, but for large data sets, that is not necessarily slower than the use of a FTP site. However, if the data sets are very large, then the client will likely have to consider a third option—a stand-alone server. There are services that will securely transport and deliver servers and racks of hard drives. Indeed, major cloud services vendors will come pick up a server and take it to their facilities for data transfer. If a stand-alone server or rack of hard drives is used, the client and analyst will also likely wish to discuss the physical security of the server during transit and at the final facilities where it will be stored, whether that is at the analyst’s facilities or the facilities of a vendor (or both).

Getting the data physically in the hands of the analyst does not mean analysis can immediately begin. The analyst must first “ingest” the data. This includes decompressing it, decrypting it, checking for corruption of files, recombining any files that were broken up for transit, and transferring all of the data into whatever hardware and software environment the analyst wishes to use. This can take weeks for big data, particularly if the analyst is relatively unfamiliar with working with such large data sets.

Basic analysis can begin once the transfer issues are resolved. The first step here is usually a cleaning process: run basic summary statistics, review outliers, identify and clean errors, etc. As part of this, the client will likely have provided anecdotes and stylized facts about what the data
show. Do the data received appear to be consistent with those anecdotes? If not, is it because there is a problem with the data or with the anecdote? For example, an analyst might have received geospatial data on the locations of stores and delivery centers. The analyst might then confirm its location accuracy, e.g., a simple test might be whether some locations are on water rather than on land; a more specific test might be to look at a sample and confirm the coordinates are in the general expected location of stores and delivery centers. Again, this process can be time consuming, generally, and is even more so with big data. For example, with ten times as many variables and ten thousand times more observations as a more conventional data set, there are likely more oddities to be explored. That does not mean big data are any less reliable, simply that the data may cover much more ground and so take more time to understand. This will likely involve considerable back-and-forth between the analyst and the client.

Next is to determine the logic for creating a “record” of each observation—the inclusion of all of the relevant data for each observation—for the analysis itself. Most data come in a form that is not immediately relevant to answer the questions that are typically asked for the purposes of an antitrust analysis. For instance, sales data often needs to be rolled up to a daily, weekly, or monthly price net of discounts and rebates. Such data are often produced in an invoice file and a rebate accrual file.

The analyst may also be considering a sampling strategy. Are the resources available to employ the full data set or will the analyst wish to extract a valid statistical sample? This is an area where even with cloud computing, using the full data set may not be practical. It will depend in large part on the question being asked. If the analysis is amenable to being done in parallel (running lots of processes simultaneously), it is more likely that cloud computing will allow even big data to be used in full. Alternatively, if the analysis requires processes to be run sequentially, one after another, the analysis of the entire data base may be too time consuming and so data aggregation or sampling techniques may be called for.

Big data can have a significant impact on processing time. In some cases, computing power has grown quickly enough that processing time can be shorter than in the past despite the size of the data set being much larger, but that depends greatly on the specific type of problem being analyzed. Consider the following example. A merger litigation several decades ago involved shop keeping unit (SKU) level sales data for two firms. The data were beyond the processing capabilities of most analysts at the time and the authors’ firm was engaged because we had a supercomputer. Even so, running a regression on the data could take upwards of 12 hours, which in the middle of litigation is an eternity.

Recently, the authors have worked with large (multiple terabyte) data sets where statistical work on local computing facilities in SAS, MS-SQL, or Stata still takes over eight hours. However, using an optimized cloud computing framework we have developed, that particular statistical work that in a local SAS, MS-SQL, or Stata environment took over eight hours now runs in only 15 seconds.\(^5\) So while it is generally the case that big data means everything takes longer and costs more, there are some exceptions.

Having resolved these various issues, the output of this process at this point will likely look familiar to all those involved. Basic charts, tables, and summary statistics are produced to get a more detailed understanding of the data and to “gut check” the data build with the client (e.g., are aver-

age prices what would be expected, are regional differences in prices reasonable, etc.). As noted earlier, big data is likely to produce models with small standard errors, so practitioners may want to inquire more closely about other measures of error, such as robustness of the results to small changes in the specification of the model, or the possibility of measurement bias. Moreover, just because a statistic is precisely measured does not mean that it is necessarily economically relevant (e.g., accounting margins and economic margins are not the same thing, and precisely measuring the accounting margin does not itself make the accounting margin a better measure of the economic margin). Similarly, even if a variable has a statistically significant impact on price, for example, it does not mean that the effect of that variable on price is quantitatively important. The effect could be trivial.

**Conclusion**

While the basic analyses today are the same whether or not big data is involved, the mechanics of engagements can differ in important ways. There are logistical challenges unique to big data, and the methodologies used in the analyses may be influenced by hardware and software limitations. Practitioners may also wish to pay less attention to standard errors and more attention to other forms of error, such as misspecification of the model.
DraftKings/FanDuel: Adventures in Challenging a Merger Using an Effects-Driven Approach

Ryan Quillian and Mark Seidman

The U.S. Supreme Court has long held that defining “the relevant market is a necessary predicate to a finding of a violation of [Section 7 of] the Clayton Act . . . .”1 Controlling Supreme Court precedent also dictates that, once product and geographic markets are defined, mergers are presumptively illegal if they (1) create a combined company with undue market share and (2) result in a significant increase in market concentration.2 Not surprisingly, when a proposed merger meets these criteria, the U.S. Federal Trade Commission3 (FTC or Commission) typically includes that argument in the complaint.4 Nevertheless, defendants in several recent merger challenges have criticized the Commission for allegedly relying solely or primarily on the structural presumption of illegality and what those defendants viewed as “artificially defined” relevant markets.5 Antitrust scholars have also questioned the assumed relationship between high market shares and reductions in consumer welfare underlying the presumption.6 Alleging that a merger meets the structural presumption does not mean that the Commission relied solely—or even predominantly—on the presumption when deciding whether to challenge the merger.7 To the contrary, the complaints filed in recent merger challenges reflect an approach that emphasizes competitive effects, while also defining relevant markets and stating whether the proposed merger meets the structural presumption of illegality.8

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3 The FTC and the Antitrust Division of the U.S. Department of Justice (DOJ) share jurisdiction over the review of mergers.
4 See Douglas H. Ginsburg & Joshua D. Wright, Philadelphia National Bank: Bad Economics, Bad Law, Good Riddance, 80 ANTIHRUSTR L.J. 201, 210 (2015) (“If the FTC, the Antitrust Division, or the occasional private plaintiff can define the relevant market and show that the market shares of the firms proposing to merge [meet the relevant criteria], then it would be folly for the plaintiff not to base its primary argument upon the [structural] presumption.”).
7 Sections 6 and 7 of their Merger Guidelines indicate that the FTC and DOJ contemplate an analysis of competitive effects beyond any structural presumption that a merger may meet. See U.S. Dep’t of Justice & Fed. Trade Comm’n, Horizontal Merger Guidelines §§ 6, 7 (2010) [hereinafter Merger Guidelines].
The Commission’s complaint challenging the merger of DraftKings and FanDuel, two providers of daily fantasy sports (DFS) contests, provides a good example of a case that may appear superficially to rely on the structural presumption but reflects an effects-driven approach to merger analysis. Although the proposed merger clearly satisfied the conditions necessary to meet the presumption of illegality, the investigation and complaint focused on the anticompetitive effects that the proposed merger would have caused and, in particular, the elimination of the intense and pervasive head-to-head competition between the merging parties.

Nevertheless, the merging parties criticized the Commission for defining the relevant product market too narrowly and relying on the structural presumption when deciding to block the proposed merger. For example, in their answers to the federal court complaint, DraftKings and FanDuel claimed:

"The underlying premises of the Complaint . . . reflect an unnecessarily rigid and uninformed application of the antitrust laws to an underdeveloped, nascent industry, and largely ignore rigorous economic analysis . . . . Plaintiffs’ challenge to the proposed transaction is not rooted in what has long been emphasized by the Horizontal Merger Guidelines, which is that the antitrust analysis of any given transaction should favor economic analysis of likely competitive effects and harm over simple market structure wherever possible.”

Joshua Wright, a former FTC Commissioner whose law firm represented FanDuel, also criticized his former agency, arguing on Twitter that the Commission defined the market “too narrowly” because there were “important constraints outside DFS,” which he viewed as “a good example of 1960s structural shortcuts suppressing economics.” In Professor Wright’s view, “shouting ‘2 to 1’ in DFS is a poor substitute for economic analysis.” Despite this criticism, DraftKings and FanDuel abandoned the transaction about one month after the Commission voted to block the merger and before the district court had ruled on the FTC’s motion for a preliminary injunction.

While there may be a tension between what the relevant statutes and case law require (i.e., market definition) and the effects-focused Merger Guidelines, that tension does not necessarily lead to different enforcement outcomes. Quite the opposite. As evidenced by the DraftKings/FanDuel investigation and litigation, market definition is just one factor in the Commission’s decisions of whether to challenge mergers—the focus is on competitive effects.

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11 https://twitter.com/ProfWrightGMU/status/883466511939117056.

12 https://twitter.com/ProfWrightGMU/status/883445608220049409; see also Joshua D. Wright, Whither Conservative Merger Policy?, NAT’L REV. (Jan. 24, 2018), http://www.nationalreview.com/article/455728/donald-trumps-antitrust-enforcement-conservative-merger-policy (“The FTC’s decision to block the DraftKings/FanDuel merger is heavily reminiscent of an Obama-era trend that too often prioritized adventurous theories over economically sound ones.”).  

13 https://twitter.com/ProfWrightGMU/status/883466511939117056.

14 DraftKings and FanDuel announced that they had agreed to merge in November 2016. The Commission’s investigation culminated in the filing of a complaint in June 2017. The merging parties announced that they had abandoned the transaction in July 2017.
Competitive Effects Alleged by the Commission in DraftKings/FanDuel

In a unilateral effects case, the key issue is the closeness of competition between the merging parties. As explained in the complaint, DraftKings and FanDuel were not only the two largest DFS providers (by far), they were each other’s closest competitor. They competed across a variety of price and non-price dimensions, and the competition between them benefited customers. The merger would have enhanced market power by eliminating competition and its benefits. The qualitative evidence described in the public version of the complaint and summarized below, some of which the merging parties contested, was corroborated by robust economic analysis.

DraftKings’ CEO believed that “[t]here is only one competitor of consequence—FanDuel” and FanDuel, likewise, viewed DraftKings as its “most significant competitor.” The competition between the merging parties was so intense that DraftKings’ senior executives described the “usual” form of competition with FanDuel as fighting tooth and nail to attract customers—to “smash them,” to put a “foot on [FanDuel’s] throat and press down hard,” and not to “let up until they stop breathing.”

This heated head-to-head competition spanned both price and non-price dimensions. On price, the merging parties were each other's primary constraint. The commission rate (i.e., the portion of entry fees that a DFS provider keeps for itself) is essentially the “list price” a DFS provider charges the user for entering a contest. The actual price paid by DFS users is largely a function of the commission rate and any discounts or acquisition, referral, and retention bonuses given by DFS providers.

DraftKings and FanDuel benchmarked their prices against each other to make sure that they did not set their commission rates higher than the other’s rates. They each feared that comparatively higher rates would drive users (particularly professional users) to shift their business to the other party. At the same time, however, DraftKings and FanDuel set their commission rates so that they were in parity with the other’s rates. Neither party engaged in similar conduct with respect to other DFS providers. In fact, the merging parties did not even track the commission

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15 DraftKings and FanDuel acknowledged that they controlled at least 90% percent of the DFS market. Public Complaint, supra note 9, ¶ 55; see also id. ¶ 57 (stating that, based on those market shares, the DFS market was already highly concentrated without the merger and that “the Merger would produce concentration levels well beyond what is necessary to establish a presumption of competitive harm”).

16 See id. ¶¶ 59–60.

17 See id. ¶¶ 1–2, 59–87.

18 The data work performed by the Commission during the investigation remains confidential, which restricts our ability to discuss it here.

19 Public Complaint, supra note 9, ¶ 60.

20 Id. ¶ 3.

21 The remainder of the entry fee goes to fund the contest’s prize pool.

22 Whether a guaranteed contest fills can also affect the effective price a user pays because the DFS provider must distribute the predetermined prize pool regardless of whether the contest fills. Therefore, the effective price in a guaranteed contest that fills is higher than the effective price in a guaranteed contest that does not fill.

23 Public Complaint, supra note 9, ¶ 68.

24 There is a small subset of users for whom DFS is a profession (i.e., DFS is their only or primary source of income). See id. ¶ 31. Compared to other DFS users, professionals tend to participate in more contests, submit higher volumes of entries, and win a greater amount of prizes. Id. It is much harder—if not impossible—to earn a living playing season-long fantasy sports contests.

25 Id. ¶ 68.

26 Id. ¶¶ 68–71.

27 See id. ¶ 70.
rates of other DFS providers with any consistency.\textsuperscript{28} DraftKings and FanDuel also sought to match or beat each other’s acquisition, referral, and retention bonuses.\textsuperscript{29} This head-to-head competition on all aspects of price led to lower prices than would otherwise have prevailed, which directly benefited customers of DraftKings and FanDuel.\textsuperscript{30}

Non-price competition between the merging parties was also intense and ubiquitous. One of the most important components of non-price competition among DFS providers is predetermined contest size (i.e., how much prize money is at stake).\textsuperscript{31} From the users’ perspective, larger contests are typically more attractive (all else being equal); however, it is riskier for DFS providers to offer larger contests. This is because many DFS contests are “guaranteed,” meaning they will occur regardless of whether the contest fills. As a result, even if a contest does not attract the maximum number of entries, the DFS provider still must pay the prize pool to the contest’s winners. In some situations, total entry fees can be less than the total prize pool, resulting in the provider running the contest at a loss. Thus, DFS users benefit from larger contests because (1) the amount of money they could win is larger and (2) the contest has the potential not to fill, which would reduce the effective commission rate for all entries into that contest and give each lineup a better chance of winning. Larger contests are riskier for DFS providers for the same reason: they are more likely not to fill, which reduces providers’ revenue and may result in offering contests that lose them money. DraftKings and FanDuel competed aggressively to offer the largest contests and frequently matched or exceeded the size of each other’s contests.\textsuperscript{32} This rivalry led both DraftKings and FanDuel to take on the risk of offering increasingly large contests.\textsuperscript{33} This is quintessentially quality competition.

Other areas of non-price competition between DraftKings and FanDuel included the development of new products and features, including the number of sports in which they offered contests.\textsuperscript{34} This innovation derived directly from head-to-head competition between the parties.\textsuperscript{35} As with price competition, DraftKings and FanDuel monitored each other’s product features and used the results to determine which features they lacked and to prioritize their product development efforts.\textsuperscript{36} In response to each other’s changes in product features or sports offerings, DraftKings and FanDuel frequently improved their own product features or expanded their sports offerings.\textsuperscript{37} In one instance, DraftKings’ CEO told his product development team that DraftKings should “outright steal [a FanDuel product feature] but let’s give it our own name!”\textsuperscript{38} Similarly,

\textsuperscript{28} Id. ¶ 70.

\textsuperscript{29} Id. ¶ 73.

\textsuperscript{30} Id. ¶¶ 73–75.

\textsuperscript{31} For most DFS contests, users pay an entry fee. The majority of those entry fees go towards a prize pool paid out to the contest winners. DFS providers generate revenue by retaining a portion of the entry fees as their commission.

\textsuperscript{32} Public Complaint, supra note 9, ¶¶ 78–80.

\textsuperscript{33} Id.

\textsuperscript{34} See id. ¶¶ 82–87.

\textsuperscript{35} See id.

\textsuperscript{36} Id. ¶¶ 83–84.

\textsuperscript{37} Id. ¶¶ 83, 87.

\textsuperscript{38} Id. ¶ 87.
FanDuel introduced new sports to keep pace with DraftKings’ offerings and to retain users’ entry fee volume.\footnote{39}

Innovation and non-price competition between DraftKings and FanDuel has continued since they abandoned the merger. For example, in October 2017, DraftKings entered a partnership to integrate live and on-demand audio on its platform; a move that FanDuel made in May 2017.\footnote{40} Non-price competition persisted throughout the investigation as well, including FanDuel’s introduction of golf DFS contests to compete directly with DraftKings’s golf offering in March 2017.\footnote{41} Similarly, FanDuel began offering WNBA DFS contests in May 2017, and DraftKings followed shortly thereafter in July 2017.\footnote{42}

This evidence of intense and pervasive head-to-head competition was consistent with the Commission’s economic analysis showing that the merger was likely to enhance market power by eliminating competition. The ordinary course evidence, investigatory testimony, and data analysis all pointed in the same direction: the proposed merger would be bad for consumers.

Daily Fantasy Sports as a Relevant Product Market

Supreme Court precedent and the Merger Guidelines both continue to include market definition as a key aspect of any Section 7 case. In addition to pleading the strong evidence that a merger between DraftKings and FanDuel would have anticompetitive effects, the Commission also defined a relevant product market. The substantial evidence of head-to-head competition and the parties’ almost singular focus on each other suggested that DFS was the appropriate relevant product market, and the Commission’s close analysis of the products at issue corroborated that conclusion.

The merging parties competed primarily against other DFS providers (mostly each other). There was scant evidence of competition against any non-DFS products, including season-long fantasy sports.\footnote{43} Indeed, the evidence showed that DraftKings and FanDuel focused their competitive energies almost exclusively on each other, which strongly suggested a DFS-only product market.\footnote{44} In addition, statements like DraftKings’ CEO’s assertion that “[t]here is only one com-

\footnote{39} Id.


\footnote{43} A relevant product market does not necessarily include all potential substitute products. As expressed in the Merger Guidelines and the case law, a relevant product market is the smallest set of products over which a hypothetical monopolist could impose a small but significant non-transitory price increase. See, e.g., Merger Guidelines, supra note 7, § 4.1.1 (“Groups of products may satisfy the hypothetical monopolist test without including the full range of substitutes from which customers choose. The hypothetical monopolist test may identify a group of products as a relevant market even if customers would substitute significantly to products outside that group in response to a price increase.”); United States v. H&R Block, Inc., 883 F. Supp. 2d 36, 54 (D.D.C. 2011) (“While providers of all tax preparation methods may compete at some level, this ‘does not necessarily require that [they] be included in the relevant product market for antitrust purposes.’” (quoting FTC v. Staples, Inc., 970 F. Supp. 1066, 1075 (D.D.C. 1997))). Nevertheless, in this instance, the evidence indicated little competition between DFS and other entertainment options.

\footnote{44} “Evidence of competitive effects can inform market definition . . . .” Merger Guidelines, supra note 7, § 4.
petitor of consequence—FanDuel)—are inconsistent with any claim that the market was broader than DFS. If there were “important constraints outside DFS,” neither DraftKings nor FanDuel was concerned about them in the ordinary course of business.47 As if to confirm the Commission’s view of the market, after the parties abandoned the merger, DraftKings’ Chief Marketing Officer stated that “DraftKings has led the way in innovation and breakthrough ideas creating the game inside the game that only daily fantasy sports can provide.”48 These and similar statements, in addition to a mountain of ordinary course evidence from the merging parties and third parties, indicated that the industry viewed DFS as a distinct market.

In addition to the competitive dynamics between the parties, the Commission identified abundant evidence that DFS was distinct from other products, most notably season-long fantasy sports. The most important qualitative differences were the draft structure and the duration of DFS contests; other differences were derivative of those two unique qualities. For example, using a salary cap draft (rather than the snake or auction drafts used in season-long)49 allowed DFS contests to be exponentially larger in terms of both the number of users who could enter (because any user could draft any athlete)50 and, relatedly, the total amount of money at stake (more users in a given contest meant larger payouts, all else being equal). Similarly, running DFS contests on a daily or weekly basis permitted users to enter a contest on almost any day of the year rather than waiting an entire sports season (i.e., six months or more) to find out the results of a contest.

These functional differences also drove—and were reflective of—users’ motivations for playing. For example, the structure of DFS gave users the opportunity to win life-changing amounts of money in a way that season-long did not. In fact, for some users, DFS was a profession—a phenomenon not seen in season-long fantasy sports, which users typically play for social reasons.51 DFS also offered instant gratification to users who may otherwise have to wait until the end of a sport’s regular season to find out who won a contest.

Of course, the existence of other forms of sports-related entertainment, including season-long fantasy sports, may theoretically constrain DFS pricing at some level.52 The key question for market definition, however, was whether season-long and other potential alternatives were sufficiently close substitutes for DFS to constrain a small, but significant, increase in DFS pricing after the pro-

45 Public Complaint, supra note 9, ¶ 60.
47 See Public Complaint, supra note 9, ¶¶ 45, 48.
49 In a snake draft, the order of selection reverses in each round (i.e., the user who picks first in round one picks last in round two and the user who picks last in round one picks first in round two). In an auction draft, users have a predetermined fictional budget that they use to bid on players until they fill their rosters.
50 DFS contests frequently had thousands or tens of thousands of entries, while the limit of entries into season-long contests was usually no more than 10 to 20, depending on the sport.
51 See Public Complaint, supra note 9, ¶¶ 20, 31, 42.
52 Cf. H&R Block, 833 F. Supp. 2d at 57 (noting that most taxpayers would switch to pen-and-paper if the price of digital-do-it-yourself and assisted products were raised to $1 million per tax return); United States v. Aluminum Co. of Am., 148 F.2d 416, 426 (2d Cir. 1945) (Even a monopolist must moderate its exertion of pricing power).
posed merger. The answer was no. Season-long fantasy sports were not a meaningful substitute for DFS. This conclusion was driven, in part, by the very economic analysis that the Commission supposedly “ignore[d]” or “suppress[ed].” For example, historical price increases showed that, at least in the past, a DFS product market satisfied the hypothetical monopolist test. In 2015 and 2016, DraftKings and FanDuel each raised their commission rates, but DFS users did not respond by substituting away from DFS to season-long fantasy sports (or to any other activity) in substantial numbers. In fact, neither DraftKings nor FanDuel observed a meaningful decrease in demand and, as a result, each saw increased revenue.

Within a DFS product market, DraftKings and FanDuel were the two dominant competitors. DraftKings and FanDuel admitted as much, describing the market as a “duopoly.” According to DraftKings’ CEO, “As everyone knows, the vast bulk of the industry is DraftKings and FanDuel.” In the ordinary course of business, DraftKings and FanDuel estimated that together they controlled at least 90 percent of DFS entry fees. Regardless of how that 90 percent broke down between the parties, the post-merger DFS market would be highly concentrated (with an HHI of at least 8,100) and it was clear that the change in HHI would well exceed 200 points. As a result, the DraftKings/FanDuel merger was presumptively illegal under the Merger Guidelines and the relevant case law. This evidence corroborated, but did not replace, a rigorous analysis of the competitive effects of the proposed merger. As the Merger Guidelines dictate, market structure is only a starting point, and it does not answer the key question of closeness of competition. The investigative record, however, left little doubt: DraftKings and FanDuel were, far and away, each other’s most significant competitor.

Conclusion

The Commission’s investigation of the DraftKings/FanDuel merger exemplified the effects-focused nature of the Merger Guidelines. Consistent with the case law on Section 7 violations, the complaint alleged a relevant product market. It would be a mistake to presume that the structure of a complaint necessarily reflects the Commission’s decision-making process. A complaint is a litigation document; its fundamental purpose is to frame the evidence and arguments in accordance with the controlling case law. As here, the Commission’s investigations follow the framework of the

54 See Public Complaint, supra note 9, ¶ 48.
55 Id.
56 Id.
57 See id. ¶ 3; see also Affidavit of Gregory B. Karamitris, Vice President of Analytics, DraftKings ¶ 5 (Nov. 23, 2015), filed in People v. DraftKings, Inc., No. 453054/2015, Doc. No. 102 (N.Y. Sup. Ct. Nov. 24, 2015) (testifying that DraftKings and FanDuel were the “[c]urrent market leaders” in DFS).
59 See Public Complaint, supra note 9, ¶ 55 (citing the parties’ ordinary course business documents showing that DraftKings and FanDuel estimated that they controlled between 93–95% of the DFS market); COM-00000197, Bain & Co., Falcon Interim Update-49 (Mar. 2, 2015), filed in People v. DraftKings, Inc., No. 453054/2015, Doc. No. 84 (N.Y. Sup. Ct. Nov. 23, 2015) (providing an estimate from a consulting firm hired by FanDuel that “[FanDuel] and Draft Kings [sic] have ~96% market share”).
60 See Public Complaint, supra note 9, ¶ 56.
61 See id. ¶¶ 57–58; Merger Guidelines, supra note 7, § 5.3; Philadelphia National Bank, 374 U.S. at 363.
2010 Merger Guidelines, which emphasize that “[t]he Agencies’ analysis need not start with market definition” and “[e]vidence of competitive effects can inform market definition . . . .”62

It is also no surprise that the Commission will go into court with its best evidence, which will typically include the structural presumption when it is met. Allegations of high market shares hardly indicate that the Commission or its staff “ignore[d]” or “suppress[ed]” economic or competitive effects evidence. As Professor Wright has noted elsewhere, “When career econ[omist]s, lawyers, and [a] unanimous FTC reach the same conclusion on an issue perhaps its [sic] not an ideological conspiracy?”63

62 Merger Guidelines, supra note 7, § 4.
63 https://twitter.com/ProfWrightGMU/status/880416302413762563.