Stanford Computational Antitrust

ARTICLE

Micro-Directives and Computational Merger Review

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Abstract. AI technologies can improve upon the current system of merger notification and review. Predictive technologies—such as supervised machine learning—combined with unprecedented growth in data will provide antitrust agencies with the opportunity to better refine the law and the review process. Such technologies will build upon how antitrust agencies already model and predict the likely consequences of mergers. Here, we explore how such predictions can reduce both the over-inclusiveness and under-inclusiveness inherent in the current system of merger notification and review. We explore the possibility of a more automated system of merger review. We argue that the greatest hurdle to the adoption of such a system is not feasibility, technological limitations, or the availability of data. Rather, the greatest hurdle is the difficulty in pinning down a precise and translatable ex ante objective that such an algorithm would optimize.

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I. Introduction

Antitrust enforcement in the United States is ramping up. Advocates on both sides of the political aisle have argued for tighter regulation of the activities of large companies, particularly those in the technology sector.[1] Recent changes to key staffing positions at the Federal Trade Commission (FTC) and the Department of Justice (DOJ) (collectively, the 'agencies') have indicated that the Biden administration is ready to undertake an aggressive approach to antitrust enforcement. One area of antitrust enforcement likely to be revised is the process of merger notification and review.[2]

In this paper, we explore how computational tools may be used to improve merger notification and review. We suggest that the current system of merger notification and review is *both* over-inclusive and under-inclusive. It requires resource-constrained antitrust agencies to review mergers that are highly unlikely to generate competition concerns. It also allows potentially anticompetitive mergers to fly under the radar.

In previous work, we have argued that data-driven prediction tools—built upon will change the substance of law and the way citizens and businesses interact with lawmakers and regulators.[3] The predictive power of supervised machine learning algorithms can help reduce both decision costs and error costs associated with lawmaking and adjudication. We predicted highly tailored laws that provide the benefits of rules (clarity and consistency), along with the benefits of standards (flexibility and dynamism). We called this new form of law, the "micro-directive."

Here, we describe how micro-directives may be used in the merger review process. The promise of well-calibrated micro-directives is that they mitigate problems of both under-inclusivity and over-inclusivity. Unprecedented growth in big data will be available to measure the impact of mergers. This will allow agencies to better predict which mergers are likely to generate anticompetitive concerns and which are not. The use of supervised machine learning algorithms to make such predictions will build upon the existing methods of retrospectively analyzing the

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[1] *See* Katie Canales*, Congress Unveils 5 Bipartisan Bills that Mark its Biggest Step Yet in Regulating Tech Giants like Amazon, Google, Facebook, and Apple,* BUSINESS INSIDER (Jun. 11, 2021), https://www.businessinsider.com/congress-big-tech-bills-facebook-google-apple-amazon-antitrust-2021-6.

[2] On July 9, 2021, the Acting Assistant Attorney General Richard A. Powers (Department of Justice, DOJ) and Lina Khan Chair of the Federal Trade Commission, FTC) called for revisions to the merger guidelines:

> 'We must ensure that the merger guidelines reflect current economic realities and empirical learning and that they guide enforcers to review mergers with the skepticism the law demands. The current guidelines deserve a hard look to determine whether they are overly permissive. We plan soon to jointly launch a review of our merger guidelines with the goal of updating them to reflect a rigorous analytical approach consistent with applicable law.'

Press Release, Fed. Trade Comm'n, Statement of FTC Chair Lina Khan and Antitrust Division Acting Assistant Attorney General Richard A. Powers on Competition Executive Order's Call to Consider Revisions to Merger Guidelines, https://www.ftc.gov/news-events/press-releases/2021/07/statement-ftc-chair-lina-khan-antitrust-division-acting-assistant (Jul. 9 2021).

[3] Anthony J. Casey & Anthony Niblett, *The Death of Rules and Standards*, 92 IND. L.J. 1401 (2017); Anthony J. Casey & Anthony Niblett, *Self-driving Laws,* 66 U. TORONTO L. J. 429 (2016).

effects of merger decisions.[4] At one extreme, micro-directives can be used to help create an automated premerger notification scheme. Parties to a transaction can enter relevant information and receive an (almost) instantaneous answer from the agencies as to whether the merger can proceed.

We are certainly not the first to suggest the use of computational methods to assist with merger notification and review.[5] In a recent paper, published in this journal, Robert Zev Mahari, Sandro Claudio Lera, and Alex Pentland (MLP) argue that computational methods can help provide an "early warning" system for anticompetitive mergers.[6] MLP investigate the evolution of networks to predict when dominant players may acquire nascent potential competitors. Under certain circumstances, the model predicts that a winner-takes-all market will emerge. The authors argue that the current thresholds of merger notification and review fail to capture some of these "killer acquisitions," particularly in the technology and health sectors.[7] In the same journal issue, Daryl Lim also suggests that computational methods can be used to model counterfactuals and prospectively identify which mergers are likely killer acquisitions.[8]

Our analysis, however, takes a broader view of computational merger review. While MLP and Lim address the problem of mitigating underenforcement, we look at the potential to better calibrate the law in *both* directions, correcting for problems of over- and under-inclusions. Such a system would reduce both false positives (denying mergers that should be allowed to proceed) and false negatives (allowing mergers that should be denied.)[9] We argue that data on market structure, conduct of firms, performance, innovation, and harms to consumers will become richer and more voluminous, allowing predictive tools to be used by agencies to better calibrate the law.[10]

But there are limits to computational merger review. There are potential limits regarding the technological feasibility, the availability of sufficient data, or people's

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[4] *See* Oliver Budzinski & Isabel Ruhmer, *Merger Simulation in Competition Policy: A Survey*, 6 J. COMPETITION L. & ECON. 277 (2010); Dennis W. Carlton, *Why We Need to Measure the Effect of Merger Policy and How to Do It*, 5 COMPETITION POL'Y INT'L 77 (2009).

[5] Or with antitrust decisions more generally. *See* Giovanna Massarotto & Ashwin Ittoo, *Gleaning Insight from Antitrust Cases Using Machine Learning*, 1 STANFORD J. COMPUTATIONAL ANTITRUST 16 (2021); Giovanna Massarotto & Ashwin Ittoo, *Can AI Replace the FTC?* (November 19, 2020), available at https://ssrn.com/abstract=3733324. The importance of having antitrust regulators that understand machine learning technologies has been recognized by regulators themselves. *See, e.g.*, Assistant Attorney General Makan Delrahim Delivers Remarks at the Thirteenth Annual Conference on Innovation Economics (Aug. 27, 2020), available at: https://www.justice.gov/opa/speech/assistant-attorney-general-makandelrahim-delivers-remarks-thirteenth-annual-conference.

[6] Robert Zev Mahari, Sandro Claudio Lera & Alex Pentland, *Time for a New Antitrust Era: Refocusing Antitrust Law to Invigorate Competition in the 21st Century,* 1 STANFORD J. COMPUTATIONAL ANTITRUST 52 (2021); *see also* Sandro C. Lera, Alex Pentland & Didier Sornette, *Prediction and Prevention of Disproportionally Dominant Agents in Complex Networks,* 117 PROC. NAT. ACAD. SCI. 27090 (2020).

[7] Mahari, Lera & Pentland, *Time for a New Antitrust Era*, 1 STANFORD J. COMPUTATIONAL ANTITRUST at 56; *see also* Colleen Cunningham, Florian Ederer & Song Ma*, Killer Acquisitions* 129 J. POL. ECON. 649 (2021) (describing killer acquisitions as incumbent firms acquiring innovative targets to discontinue the target's projects and lessen competition).

[8] Daryl Lim, *Can Computational Antitrust Law Succeed?*, 1 STANFORD J. COMPUTATIONAL ANTITRUST 38 (2021).

[9] *See* Frank H. Easterbrook, *The Limits of Antitrust*, 63 TEX. L. REV. 1, 1 (1984); Jonathan B. Baker, *Taking the Error Out of "Error Cost" Analysis: What's Wrong With Antitrust's Right*, 80 ANTITRUST L.J. 1 (2015).

[10] The computational tools discussed by MLP and Lim can certainly provide one input into a computational merger review algorithm by forecasting what market concentration will look like in the near future if a merger is allowed to proceed.

willingness to place trust in a fully automated computational merger review system. For the most part, we view these challenges as surmountable.

For us, the major challenge to *fully automated* computational merger review—and perhaps all of computational antitrust law—is the difficulty in specifying the objective that an AI-infused algorithm should optimize.[11] Micro-directives in merger review would require a clear objective function. But what if there is little consensus as to what that objective function is?

Indeed, many of the recent calls for a more aggressive approach to mergers in the United States are centered on the idea that the agencies have sought the wrong objectives.[12] While some have argued that antitrust agencies should continue to look at economic harms to consumers—but do so more aggressively—others have suggested a broader set of objectives. They have argued that antitrust law should seek to achieve broader social goals, such as maximizing fairness, minimizing inequality, minimizing privacy harms, fostering free speech, or promoting a healthy democracy.[13]

Things get complicated when one considers the full scope of potential objectives for antitrust law. In the United States, the putative objective of antitrust law has changed markedly over time. And the current goal of maximizing consumer welfare—which is professed by agencies and found in the controlling doctrine—has many dimensions and lends itself to many interpretations.[14] Looking further afield, antitrust authorities around the world seek a broad and diverse range of potential objectives for competition law and in regulating markets.

Questions remain about how these various possible objectives are to be balanced *ex ante*. Fully automated computational merger review would require a clearly stated choice among competing views of antitrust law. The reviewing agencies must be explicit about what ends they are pursuing and how they prioritize competing values.

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This paper is structured in the following way. In Part 2, we briefly describe the current regime of merger notification and review and discuss key critiques of that regime. In Part 3, we describe how micro-directives might work to improve the current system. We explore the possibilities for an automated merger notification

[11] We made a similar point in the context of 'personalized rules' in Anthony J. Casey & Anthony Niblett, *A Framework for the New Personalization of Law*, 86 U. CHI. L. REV. 333 (2019).
[12] *See e.g.*, Lina M. Khan, *Amazon's Antitrust Paradox*, 126 YALE L.J. 710 (2017) (arguing that the current framework in antitrust is not suited to deal with the architecture of market power in the modern economy, using Amazon's dominance as an example).
[13] *See e.g.,* Maurice E. Stucke, *Reconsidering Antitrust's Goals*, 53 B.C. L. REV. 551 (2012); Tim Wu, *After Consumer Welfare, Now What? The 'Protection of* Competition' in Practice, CPI ANTITRUST CHRONICLE (2018); *Competition for the Twenty-First Century: The Case for Antitrust Reform*, Testimony by Barry C. Lynn before the Senate Committee on the Judiciary Subcommittee on Antitrust, Competition, and Consumer Rights (March 11, 2021); *Grassley on Big Tech Interfering with Free Speech,* Prepared Floor Remarks by Senator Charles Grassley of Iowa, April 12, 2021 available at: https://www.grassley.senate.gov/news/remarks/grassley-on-big-tech-interfering-with-free-speech.
[14] *See* Barak Y. Orbach, *The Antitrust Consumer Welfare Paradox*, 7 J. COMP. L. & ECON. 133 (2011) (discussing the limitations of the consumer welfare standard).

and review scheme. In Part 4, we examine some of the key challenges and roadblocks to implementing such a system, with a key focus is on the difficulty of specifying the objective of antitrust law up front.

II. The Current Regime of Merger Notification and Review

In this Part, we provide a high-level overview of the current regime of merger notification and review in the United States. For simplicity of analysis, we break this process into two major steps, though we acknowledge there are several interim stages along the way.

The first step is *mandatory notification*, where parties are required to notify the DOJ and FTC about the proposed transaction. Section 7A of the Clayton Act—the Hart-Scott-Rodino Antitrust Improvements Act ('HSR Act')[15]—sets out the relevant pre-merger notification regime. Parties to transactions that meet certain thresholds are required to file HSR notification forms with the FTC and the DOJ. This pre-merger notification regime is inherently 'rule-like,' as the thresholds are bright-line metrics.

The second step is the *substantive test*. Mergers in the United States are principally governed by Section 7 of the Clayton Act.[16] Transactions are prohibited if 'the effect of such acquisitions may be substantially to lessen competition, or to tend to create a monopoly.' Additional laws such as Section 2 of the Sherman Act (prohibiting monopolization) may also apply to transactions.[17] The DOJ and FTC have implemented some rules to triage this investigation. But, ultimately, the laws determining whether a merger can proceed or not are more "standard-like," turning on vague legal terms that require interpretation from regulators and adjudicators.[18]

We examine these two steps in turn, highlighting critiques leveled at each.

Step 1: Pre-merger notification

Notification is mandatory if a merger transaction meets threshold requirements and does not qualify for an exemption.[19] A transaction triggers pre-merger notification if it meets the following criteria:[20]

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[15] 15 U.S.C. § 18a.
[16] 15 U.S.C. § 18.
[17] 15 U.S.C. § 2; *see also* 15 U.S.C. § 1 (prohibiting restraints of trade); 15 U.S.C. § 45 (prohibiting unfair methods of competition).
[18] *See* Matthew Jennejohn, *Innovation and the Institutional Design of Merger Control,* 31 J. CORP. L. 101 (2015) (noting both the uncertainty of merger review when the parties are in technology markets and the entrepreneurial, experimental approach taken by agencies when reviewing such mergers.)
[19] *See* 15 USC § 18a; 16 CFR § 802 for the exemption rules. Exceptions to this regime include transactions where the goods or realty are acquired in the ordinary course of business under Section 802.1. Those transactions are deemed unlikely to violate antitrust laws. There are other exemptions for acquisitions solely for the purpose of investment if the acquirer holds ten percent or less of the issuer under Section 802.9, for acquisitions of certain real property assets such as office, residential, or agricultural property under Section 802.2, and for acquisitions of certain foreign assets under Section 802.50.
[20] The minimum dollar thresholds under the HSR Act are adjusted annually based on changes in GDP. The following are the thresholds for 2021, effective as of March 4, 2021. *HSR threshold adjustments and*

The Commerce Test: One party to the transaction is engaged in commercial activity; *and*

The Size-of-Transaction Test: *Either*
(a) the value of the transaction is greater than $368 million; *or*
(b) the transaction is valued between $92 million and $368 million, *and* the parties meet the **Size-of-Person Test**:

The Size-of-Person Test: *Either*
(a) a firm with at least $184 million in assets or annual net sales acquires a target with at least $18.4 million in total assets; *or*
(b) where the target is engaged in manufacturing, a firm with $184 million in assets or annual net sales acquires a target with at least $18.4 million of annual net sales; *or*
(c) a firm with at least $18.4 million in total assets or annual net sales acquires a target with at least $184 million in total assets or annual net sales.

With the exception of the commerce test (which is likely so broad that it will be met in nearly all cases),[21] these threshold requirements are clear bright-line rules. These bright-line rules offer clarity and predictability about which transactions need to be reported. But many commentators have noted problems with using bright-line rules as proxies or screens for competitive harm. Importantly, as is often the case with bright-line rules, they are both over-inclusive and under-inclusive. That is, they allow some problematic mergers to go through without review while imposing onerous reviews on other mergers that should present no issue.

With regard to *over-inclusion*, some commentators argue that the thresholds are set too low and capture too many transactions.[22] The concern is that merging parties are required to report too many “inconsequential” transactions. Over the past two decades, the DOJ and FTC have received an average of over 1,600 reports of transactions each year. About 97% of these notified transactions are cleared without a second request for more information. Typically, only about 2% of reported transactions are challenged by a regulator.[23]

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reportability for 2021, Fed. Trade Comm’n. (Feb. 17, 2021), https://www.ftc.gov/news-events/blogs/competition-matters/2021/02/hsr-threshold-adjustments-reportability-2021.

[21] *See* Charles W Smith & Robert A Lipstein, *Premerger Notification: Coverage, Corporate Planning, and Compliance*, 47 ANTITRUST L.J. 1181, 1195 (1979) (“As a practical matter, the commerce test will be satisfied in nearly every transaction”).

[22] *See, e.g.*, John Warren Titus, *Stop, Look and Listen: Premerger Notification under the Hart-Scott-Rodino Antitrust Improvements Act*, 1 DUKE L.J. 355 (1979) (arguing that the regime places too heavy a burden on firms and may disrupt procompetitive transactions); Hugh Latimer, *A Case of Runaway Regulation: Premerger Notification* 3 REGULATION 46 (1979) (arguing the thresholds were too low and captured too many transactions.) But note that these criticisms came prior to the 2000 amendment that adjusted the HSR thresholds upwards. For criticisms of the over-inclusiveness of thresholds following the amendment, *see* Andrew G Howell, *Why Premerger Review Needed Reform - and Still* Does, 43 WM. & MARY L. REV. 1703 (2002).

[23] These figures come from the Annual Competition Reports published jointly by the FTC and DOJ, https://www.ftc.gov/policy/reports/policy-reports/annual-competition-reports. FED. TRADE COMM’N & DEPT. OF JUST., ANNUAL REPORT NO. 42, HART-SCOTT-RODINO ANNUAL REPORT, FISCAL YEAR 2019 (2019).

Some argue that overinclusion places too great of a burden on companies and may disrupt—or even chill—procompetitive transactions.[24] It imposes unnecessary filing fees and administrative costs of providing notice.[25] There is also a 30-day waiting period that the parties must abide by until the DOJ and FTC decide that no further action will be taken. The parties are prohibited from moving forward during that waiting period. Further, there are significant costs for the DOJ and the FTC. Investigating a merger that meets the threshold but is highly unlikely to be found to substantially lessen competition is a waste of resources for underfunded agencies.

On the other side of things, some argue that these bright-line thresholds are also under-inclusive. Some mergers that fly under the radar will still significantly harm consumers. For example, these thresholds may permit "stealth consolidations."[26] Thomas Wollman offers the example of a local funeral service market where even a merger-creating monopoly may not trigger notification.[27] Recent work in economics has highlighted the deleterious effects of "killer acquisitions," particularly with mergers that fall just short of the notification thresholds.[28]

The *under-inclusivity* of the notification regime has raised significant concerns in the digital economy. Acquisitions by big tech companies of nascent rivals who are small, but capable of vigorous and disruptive competition, may escape review.[29] Bruce Hoffman, the former director of the FTC's Bureau of Competition, has acknowledged that acquisitions of such competitors in the digital economy often fall far below the HSR thresholds.[30] But Hoffman dismisses the idea that the thresholds should generally be lowered to catch these transactions, as well as the idea that the thresholds should be lowered specifically for digital or tech transactions. Instead, he suggests that anticompetitive nascent acquisitions must be detected the "old-fashioned way": keeping an ear to the ground and asking participants in various industries to spot problematic acquisitions and bring them to the authorities' attention.[31]

Over-inclusion and under-inclusion are not mutually exclusive. Indeed, they are unfortunate hallmarks of bright-line rules that try to capture complex behavior.

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[24] *See* Joe Sims & Deborah P Herman, *The Effect of Twenty Years of Hart-Scott-Rodino on Merger Practice: A Case Study in the Law of Unintended Consequences Applied to Antitrust Legislation*, 65 ANTITRUST L.J. 865 (1997).

[25] In addition to initial filing fees and delays, benign transactions selected for second requests are subject to further costs and delay. Several scholars have criticized the current second requests system. *See e.g., Id.;* William Blumenthal, *Market Imperfections and Overenforcement in Hart-Scott-Rodino Second Request Negotiations*, 36 ANTITRUST BULL. 745. (1991); Matthew S. Bailey, *The Hart-Scott-Rodino Act: Needing a Second Opinion About Second Requests*, 67 OHIO ST. L.J. 433 (2006).

[26] *See* C. Scott Hemphill & Tim Wu, *Nascent Competitors,* 168 U. PA. L. REV. 1879 (2020); Thomas G. Wollmann, *Stealth Consolidation: Evidence from an Amendment to the Hart-Scott-Rodino Act*, 1 A.E.R.: INSIGHTS 77 (2019).

[27] Thomas G. Wollman*, Stealth Consolidation*, 1 A.E.R.: INSIGHTS at 77-78.

[28] *See* Cunningham, Ederer & Ma, *supra* note 7 (discussing killer acquisitions in the pharmaceutical industry).

[29] *See* Ramírez Imanol, *Merger Thresholds in the Digital Economy*, 45 DEL. J. CORP. L. 433 (2021) (arguing that traditional notification rules do not effectively address the trend of large technology companies acquiring nascent competitors who are small, but highly capable and disruptive).

[30] D. Bruce Hoffman, Fed. Trade Comm'n, Antitrust in the Digital Economy: A Snapshot of FTC Issues, Remarks at GCR Live Antitrust in the Digital Economy Fed. Trade Comm'n (May 22, 2019), available at https://www.ftc.gov/public-statements/2019/05/antitrust-digital-economy-snapshot-ftc-issues.

[31] *Id.* at 7.

The system cannot be fixed by simply moving the line. Lowering thresholds reduces under-inclusion but exacerbates the problems of over-inclusion. The opposite is true if raising thresholds. The source of the problem is the use of blunt proxies. While the size of parties and the size of transactions are no doubt positively correlated with the likelihood of harm to competition, the idea that these simple proxies, by themselves, accurately capture economic harms is misleading.

Step 2: Substantive test

When parties notify the DOJ and FTC of the merger, the agencies assess the anticompetitive concerns that may be raised by the merger. The substantive tests used have both rule-like and standard-like elements.

First, consider the more rule-like elements used by the DOJ and FTC to screen whether a proposed horizontal merger transaction should be challenged. Once the appropriate product market and geographic market have been defined, the regulator will determine both the *level* of concentration in the market and the *change* in concentration that will result if the merger proceeds. These levels and changes are measured using the Herfindahl-Hirschman Index (HHI). Relying on simple thresholds, some mergers are deemed likely to fall within a safe harbor, while some other mergers are presumed likely to concentrate market power.[32]

Under the current version of the Horizontal Merger Guidelines, there are thresholds where the agencies are unlikely to take further action. For example, the agencies have indicated that mergers that will result in only a "small change in concentration" (one where the change in HHI is less than 100 points) or an "unconcentrated" post-market merger (one where the level of HHI is less than 1500), are "unlikely to have adverse competitive effects' and will 'ordinarily require no further analysis."[33] These threshold harbors have been criticized by some authors on the grounds that they screen out a number of mergers that nonetheless result in competitive harm.[34]

Further, there are thresholds for identifying which mergers should likely be challenged. For example, where the market is "highly concentrated" (with HHI over 2500) and the change in HHI as a result of the merger is greater than 200, the merger is "presumed" likely to enhance market power.[35]

The agencies contend that "the purpose of these thresholds is not to provide a rigid screen to separate competitively benign mergers from anticompetitive ones."[36] But they do note the strong relationship between concentration and the impact upon market power as a justification for the thresholds and presumptions.[37]

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[32] U.S. Dep't of Justice & Fed. Trade Comm'n, *Horizontal Merger Guidelines* (2010), available at: https://www.justice.gov/sites/default/files/atr/legacy/2010/08/19/hmg-2010.pdf
[33] *Id.* at 19.
[34] *See* John E. Kwoka, Jr., *The Structural Presumption and the Safe Harbor in Merger Review: False Positives, or Unwarranted Concerns?*, 81 ANTITRUST L.J. 837 (2016).
[35] DOJ & FTC, *supra* note 32, at 19.
[36] *Id.* at 19.
[37] The fascinating history and evolution of the agencies' screens and presumptions is discussed in Steven C. Salop, *The Evolution and Vitality of Merger Presumptions: A Decision-Theoretic Approach*, 80 ANTITRUST L. J. 269 (2015).

Beyond these screening thresholds, the final merger review turns on a standard. The FTC and the DOJ will consider whether a proposed transaction may substantially lessen competition or whether it will tend to create a monopoly. The agencies note that assessing this standard is: "a fact-specific process through which the Agencies, guided by their extensive experience, apply a range of analytical tools to the reasonably available and reliable evidence to evaluate competitive concerns in a limited period of time."[38]

The evidence used by the agencies in assessing the anticompetitive effects of mergers can be both *quantitative* and *qualitative.* Such evidence could include information about market shares and concentration, the degree to which the two parties engage in head-to-head competition, the existence of powerful buyers, the prospects of future entry, or whether one of the parties is a "maverick" firm with the potential for disruptive force that is being acquired by a firm with a strong incumbency position. Evidence may be sought from the merging parties, competitors of the merging parties, customers in the market, or other industry observers. Where a merger has already been consummated, the agencies will also use evidence of its actual effects.

Following assessment of this evidence, the agencies may also take into account efficiencies created by the merger and the likelihood of firm failure or assets exiting the industry. Those factors may weigh in favor of allowing the merger to proceed even if there are adverse effects on competition.

Some commentators have criticized the approach to merger review in the United States as being too permissive. Only 2% of the mergers that are notified to the DOJ and FTC are challenged. That averages to about 36 challenged mergers each year over the past two decades.[39]

Lawrence Frankel argues that the deck is stacked against enforcement.[40] He suggests there are more false negatives than false positives in the US merger review system because a determination against allowing the merger is subject to judicial review, while approval of a merger is not.[41] Further, the non-deferential judicial review may lead courts to overturn agency decisions more frequently than they should.

Other commentators have suggested that courts and agencies are likely to favor false negatives under the (perhaps misguided) belief that restricting procompetitive transactions will result in a permanent loss of benefits, but anticompetitive conduct will be resolved eventually by the market's self-correcting nature.[42] The perception that the merger control regime is "overly-permissive" has been offered as a reason

[38] *Id.* at 1.
[39] DOJ & FTC, *supra* note 23.
[40] Lawrence M. Frankel, *The Flawed Institutional Design of U.S. Merger Review: Stacking the Deck against Enforcement*, 2008 UTAH L. REV. 159 (2008).
[41] *Id.* at 159-160.
[42] *See* Alan Devlin & Michael Jacobs, *Antitrust Error*, 52 WM. & MARY L. REV. 75 (2010). Peter Carstensen (2018) has raised similar points about the relative costs of over-enforcement and under-enforcement. Peter C. Carstensen, *Merger Guidelines and the Limits of Our Understanding*, 53 REV. INDUS. ORG. 477 (2018).

for the growth of "superstar firms" with increased pricing power.[43] It no doubt underpins the calls for changes to the merger review guidelines.

III. Computational Merger Review with Micro-Directives

A – Improving merger review with micro-directives

With computational merger review, the two parties who wish to enter into a transaction enter their information into a classifier program. Taking into account all the facts entered by the parties, as well as all the information about the market that the agency has in the system, the classifier program makes predictions about likely outcomes if the parties merge. For example, the classifier may be programmed to report the likelihood of significant and durable price increases if the merger is allowed to proceed. This report can be translated into a final determination communicated to the parties or as guidance that the agencies use to make their final determination.

Under a fully automated system, the parties can be told instantaneously whether their merger is deemed likely to substantially lessen competition. Transactions that are at high risk of generating competitive concerns can be flagged instantaneously, providing these parties with information that may deter them from moving further down the road. Proposed mergers that are at low risk of such concerns may be given an instant green light to proceed. Taken to the extreme limit, micro-directives would provide a solution to the uncertainty problem facing agencies.[44]

This hypothetical may not seem technologically feasible given the highly fact-specific context of merger review. What drives our prediction – that such computational antitrust tools will be technologically feasible – is the rapid growth in data. While agencies are currently limited in the type of data they receive from merging parties, the data that will be more broadly available as inputs continue to grow. Agencies continue to amass more data on pricing, market shares, concentration, market structure, countervailing power, innovative activity, and so on. This volume of relevant data is only going to increase as the cost of collecting, storing, processing, analyzing, and using data continue to plummet.

Such data, we suggest, will form the backbone of computational merger review. Data can be retrieved on mergers that were reviewed by the agencies as well as on non-notified mergers. These data can help agencies assess how markets evolve and better understand the consequences when two firms become one.

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[43] *See* Tommaso M. Valletti & Hans Zenger, *Increasing Market Power and Merger Control*, 5 COMPETITION L. & POL. DEBATE 26. (2019); Carl Shapiro, *Protecting Competition in the American Economy: Merger Control, Tech Titans, Labor Markets*, 33 J. ECON. PERSP. 69 (2019); Germán Gutiérrez & Thomas Philippon, *How European Markets Became Free: A Study of Institutional Drift,* NBER Working Paper No. 24700 (2018); Tim Wu, THE CURSE OF BIGNESS: ANTITRUST IN THE NEW GILDED AGE (2018).

[44] *See* Jennejohn, *supra* note 18; Geoffrey A. Manne & Joshua D. Wright, *Introduction* to COMPETITION POLICY AND PATENT LAW UNDER UNCERTAINTY: REGULATING INNOVATION 1 (Geoffrey A. Manne & Joshua D. Wright eds., Cambridge Univ. Press 2011) ("[T]he ratio of what is known to what is unknown with respect to the relationship between innovation, competition, and regulatory policy is staggeringly low. In addition to this uncertainty concerning the relationships between regulation, innovation, and economic growth, the process of innovation itself is not well understood.")

We envision a series of classification algorithms that help predict the "risk" of competitive concerns.[45] These risk assessments would help determine whether the merger can be cleared or whether more information is required. The classification algorithms provide not only the most likely risk classification, but the probability that the merger falls within that classification. If a merger is predicted to have a sufficiently low risk of competitive concerns, parties could receive instantaneous clearance.

In this sense, a classification of "low risk" is somewhat analogous to falling under the notification threshold or being found to be in a safe harbor. But the classification would be based on a sophisticated predictive algorithm, fueled by all relevant data that are used in determining the effects on competition. The "rules" are flexible; they turn on the circumstances. This provides a more precisely calibrated result than the current process where notification clearances are provided based on crude proxies such as the size of the parties, the size of the transaction, or HHI.

To be clear, we are not suggesting that party size, transaction size, and HHI are not important. On the contrary, these variables may be predictive of the ultimate outcome. But they are both over-inclusive and under-inclusive and cannot adequately capture the relevant factors and likely effects of a merger. More data are needed to better calibrate the outcome.

Indeed, the data inputs could include new computational methods that forecast how a market will shake out if a merger is allowed to proceed—or how it will shake out if it is denied.[46] Projected market concentration would indeed be informative, but it would not be sufficiently informative to form the sole basis of a computational merger review scheme. There may be oligopolies dominated by a small number of players that are characterized by vigorous competition and there may be markets with a greater number of players content to engage in very soft competition.

B – How these predictive algorithms would work

The question of how these algorithms would work depends on the type of data used in making the prediction. There are two *broad* categories of data that may prove useful. The first category of data is internal to the agencies. These data may be used to replicate the decisions of the agencies. The second category of data looks at the consequences of prior mergers that have been allowed to proceed.

I. Internal agency data: Replication of agencies' past decisions

Between them, the DOJ and FTC have data on tens of thousands of mergers that have been reviewed. Between 2001 and 2020, over 30,000 transactions were

[45] This type of prediction builds on what some antitrust authorities already do in assessing the standard. Antitrust authorities use merger simulation models to help inform their final decision. Such simulations use data and economic models to predict the anti-competitive effects of a merger. See *supra* note 4.
[46] *See* Mahari, Lera & Pentland, *supra* note 5.

reported to the agencies under the notification regime.[47] The agency's information about these transactions can be used to create a dataset that essentially describes how the agencies make their decisions.[48] Supervised machine learning algorithms can then be used to predict how an agency will likely respond to a new transaction.

The data can likely provide agencies a good sense about which types of transactions are unlikely to need a second request or which are highly unlikely to be challenged. Agencies can develop such a dataset and use predictive algorithms to determine whether a proposed merger is one they would have allowed in the past.[49] In some sense, the use of this data can "predict" what the agency will do—or, rather, replicate the decision-making process that the agency has followed in the past.[50] Use of such an algorithm would promote consistency across time and across different units and reviewers.

Such an algorithm would also allow for faster decision-making. Instead of a thirty-day waiting period, the algorithm would return an answer almost instantaneously. In doing so, the algorithm would address a problem with the notification thresholds being over-inclusive. The thirty-day waiting period for review is wasteful for mergers that meet the HSR thresholds and require notification even though the agency will almost certainly allow the merger to proceed.

The algorithm would also address under-inclusion by identifying previously unidentified factors and patterns that are relevant to the agency decision. These newly identified factors and patterns would replace the blunt proxies the agencies have used in the past. The new system would flag transactions with certain characteristics that have led lock past transactions even if the new transaction fell under the current system's blunt thresholds.

These types of algorithms are, however, only useful if we, as a society, agree that the agencies have been getting it mostly right in the past. After all, the system is intended to replicate these past decisions. This method will entrench and concretize existing patterns of enforcement. It would better reflect the stability that has been observed in merger law more generally.[51]

[47] *See* DOJ & FTC, *supra* note 23. The number of reported transactions between 2001 and 2020 according to agency records is 31,411.

[48] Similar techniques have been used in tax law to predict the outcomes of judicial decisions. *See* Benjamin Alarie, Anthony Niblett, & Albert H. Yoon, *Using Machine Learning to Predict Outcomes in Tax Law*, 58 Can. Bus. L.J. 231 (2016).

[49] Indeed, the agencies do conduct retrospective reviews of merger decisions to improve policies. *See* Rebecca Kelly Slaughter, Commissioner, Fed. Trade Comm'n, *Merger Retrospective Lessons from Mr. Rogers,* Remarks at the Hearings on Competition & Consumer Prot. in the 21st Century: Merger Retrospectives (Apr. 12, 2019). The feasibility of detailed 'retrospective' merger reviews is critiqued in Karen Hoffman Lent & Kenneth B. Schwartz, *A Caution for Retrospective Merger Reviews,* MONDAQ (May 29, 2019), https://www.mondaq.com/unitedstates/maprivate-equity/809820/a-cautionfor-retrospective-merger-reviews.

[50] *See* Benjamin Alarie, Anthony Niblett, & Albert H. Yoon, *Regulation by Machine*, MACH. LEARNING & L. (2016), https://www.mlandthelaw.org/papers/alarie.pdf. Paper delivered at 30th Conference on Neural Information Processing Systems (NIPS 2016), Barcelona, Spain.

[51] *See* HERBERT HOVENKAMP, THE ANTITRUST ENTERPRISE: PRINCIPLE AND EXECUTION 208 (2005) (noting that "merger law today is fairly stable"); Louis Kaplow & Carl Shapiro, *Antitrust*, *in* 2 HANDBOOK OF LAW & ECONOMICS, 1161 (A. MITCHELL POLINSKY & STEVEN SHAVELL EDS., 2007) ("Since the mid-1970s, there have not been further merger opinions by the Supreme Court.").

If, however, the agencies have set the bar for challenging mergers too low or too high (as some have argued),[52] then this sort of predictive exercise has significant limits. To address these concerns, we need to look further afield for data that better capture the effects of mergers and the *consequences* of the agencies' decisions.

II. Data on consequences: Predicting likely effects on competition

The second category of data looks at the consequences of mergers that have taken place.[53] Such data can be used to develop risk assessments of mergers and acquisitions, based on various features of the firms and markets.[54] The prediction exercise here is forecasting what will happen to competition in the event the merger is cleared. These data are broad, taking into account pricing, changes in output, entry and exit, and innovative responses in the many thousands of mergers that occur. Such data better enable the agencies to ascertain where "errors" may have been made in the past, where regulators were too lenient or perhaps too stringent.

Importantly, the data should not be limited to those mergers that came across the agencies' desks. The data should include information about the effects of acquisitions that did not trigger any notifications under the HSR Act. MLP suggest that "at least half of all mergers [in 2019] did not meet the premerger reporting threshold" in their analysis of private mergers in health and technology markets.[55]

The data will not just allow agencies to learn about the errors they have made but will also track the errors that emerge as a result of the under-inclusiveness of the notification regime. By creating datasets that track the effects and consequences of all mergers— including ones that flew under the notification radar—agencies will be able to better understand where errors are being made. The machine learning algorithm will enable the agencies to better predict the consequences of allowing a merger to proceed (for example, whether it will result in higher prices, lower quality, or reduced services).

There are, of course, challenges with data. The first concern may be that agencies currently do not have sufficiently rich data at the level of the individual firms about products, performance data, or other metrics.[56] Such data are currently not publicly available. But, in the near future, we suspect that the vastly increased capacity to collect, process, and analyze data that *are* publicly available will enhance the agencies' ability to make inferences.

A second drawback is that, even with complete data on the effects of challenged mergers, a naïve algorithm that only aggregates data on mergers that have been reviewed and challenged may result in a selection problem.[57] The problem, here, is

[52] *See* Titus; Latimer; Howell, *supra* note 22.
[53] The benefits of machine learning in reducing decision errors in this way have been documented in bail decisions. *See, e.g.,* Jon Kleinberg, Himabindu Lakkaraju, Jure Leskovec, Jens Ludwig & Sendhil Mullainathan, *Human Decisions and Machine Predictions*, 133 Q. J. ECON. 237 (2018).
[54] *See* Carlton, *supra* note 4, for discussion of analyzing the 'effects' of merger policy.
[55] Mahari, Lera & Pentland, *supra* note 5, at 56
[56] John E. Kwoka Jr, *Does Merger Control Work? A Retrospective on U.S. Enforcement Actions and Merger Outcomes*, 78 ANTITRUST L.J. 619 (2013).
[57] *See* Carlton, *supra* note 4, at 82.

that ‘controversial’ mergers are more likely to be oversampled and, as such, may provide inaccurate assessments of how the agency would approach less controversial issues that are under-sampled in the data. Correcting for this selection bias will be imperative.[58]

A third drawback is that the data are asymmetric. Identifying which allowed transactions should have been blocked is easier than identifying which blocked transactions should have been allowed. When a benign transaction is blocked, no counterfactual evidence exists to show that it would have been benign. Data scientists have, however, engineered ways – albeit imperfect – to account for this asymmetry through simulation and modeling.[59]

With enough good data, these machine learning algorithms do offer enormous promise. But, as we highlight in Part 4, the key concern will be in determining what an “error” is. How can we, as a society, achieve consensus about the types of mergers we should be allowing and the types that should be denied?

* * *

The two different data sources discussed here pave the way for different types of predictions and different types of computational tools. If the dataset tracks and classifies the past decisions of the agency, then a predictive algorithm that incorporates these data will seek to mirror these decisions. The algorithm would do so faster and with greater consistency than the current system. But, if the standard of review changes, then the output of this algorithm is of little help.

Using data that explores the effects of mergers is more versatile. It can help us better understand the impact of agency decisions. From these data, a predictive algorithm can assess the risk of mergers, flagging those that are likely to result in competitive harms. It can improve not just the administration of the law, but the content of the law as well.

C – Implementation: triage or full automation?

To what extent does computational merger review require a human in the loop? Can agencies fully automate the process, or should the algorithms simply provide background predictions that human decision makers refer to in making their decisions?

The current system of pre-merger notification can be thought of as a system of triage. The notification scheme relies on very coarse “algorithms,” based on the size of parties and the size of the transaction. They are simply a way to differentiate between those mergers that require agency review and those that are unlikely to raise competitive concerns. Upon review, within the thirty-day waiting period,

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[58] *See* Malcolm B Coate, *A Meta-Study of Merger Retrospectives in the United States* (2013), available on SSRN at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2333815 (“to undertake a credible test of merger policy, it is necessary to use some control for the likelihood that the merger itself was anticompetitive in the analysis” at 2.)
[59] *See, e.g.,* Kleinberg et al, *supra* note 46.

there are further processes of triage.[60] The agencies allow many notified mergers to proceed while seeking further information about a small number of cases.[61]

Computational merger review can also function as a system of triage. Computational merger tools will be used as pre-screening devices, informing a human reviewer of a predicted risk assessment for each merger. The degree of triage would depend on the accuracy of the algorithm and the degree to which the agencies trust the risk assessment tool. That is, there may be mergers which clearly do not require further investigation or review by humans. The classification algorithm would predict that these mergers are so highly likely to be cleared that the decision needs no further examination by a human reviewer.

As the agencies become more comfortable with the use of such algorithms, the system may return an instantaneous answer to the transacting parties for outlying "easy" cases, reducing the costs of delay experienced under the current system (as well as reducing the agencies' costs). And as the comfort level grows, the number of cases in this category should also increase.

But machine learning assessments still make errors. Data may be incomplete; predictive algorithms may not capture the full picture; algorithms may entrench bias.[62] An important question is what the system will tolerate. Another important question is how agencies "weigh" the errors. Critics of the current system suggest that agencies place too much weight on the possibility of false positives compared to false negatives.[63] The degree of error that the agencies are willing to tolerate may raise additional questions of trust and legitimacy in an algorithmic system.[64]

Indeed, there are numerous challenges to implementing the use of micro-directives in merger review. But it is unlikely that the biggest hurdle to the implementation of fully automated merger review will be related to issues of technological feasibility, trust, or legitimacy. In the next Part, we spell out what we see as the greatest challenge to implementing micro-directives in merger review.

[60] *See* Jennejohn, *supra* note 18, at 130-141 (discussing the HSR process); William Blumenthal, *Market Imperfections and Overenforcement in Hart-Scott-Rodino Second Request Negotiations;* 36 ANTITRUST BULL. 745 (1991); Matthew S. Bailey, *The Hart-Scott-Rodino Act: Needing a Second Opinion About Second Requests,* 67:2 OHIO ST. L. J. 433 (2006).
[61] Second Requests are initiated in only around 3% of transactions. *See* DOJ & FTC, *supra* note 20.
[62] Daryl Lim outlines these limitations and more. Lim, *supra* note 7, at 47-49, 51. More generally on these issues, *see* Thomas Nachbar, *Algorithmic Fairness, Algorithmic Discrimination,* 48 FLA. ST. UNIV. L. REV. (forthcoming 2021).
[63] *See* Devlin & Jacobs, *supra* note 42, (refuting claim that false negatives are preferable to false positives and arguing that preferability towards either false positives or false negatives needs to be context specific); Carstensen, *supra* note 42, (comparing the 1968 Merger Guidelines and the 2010 Guidelines to suggest that there has been a shift towards the under-enforcement of mergers, but presenting empirical evidence that indicates that under-enforcement errors are more costly than over-enforcement errors); Kwoka, *supra* note 34 (arguing that courts and agencies are increasingly concerned with false positive errors, resulting in more permissive antitrust policies); Frankel, *supra* note 40 (discussing institutional causes behind the higher number of false negatives than false positives in the merger review system).
[64] *See, e.g.,* Deven R. Desai & Joshua A. Kroll, *Trust but Verify: A Guide to Algorithms and the Law,* 31 HARV. J. L. & TECH. 1 (2017); Richard M. Re & Alicia Solow-Niederman, *Developing Artificially Intelligent Justice,* 22 STAN. TECH. L. REV. 242 (2019).

IV. The Challenge of Defining a Precise Objective of Merger Review

Automated merger review presents a challenge for antitrust agencies that has, to now, been relatively easy to set aside for a later date: What is it, *exactly*, that we want merger law to achieve? What is it that we want to maximize? While American scholars and lawyers may simply respond to this question by saying "maximize consumer welfare," this objective is still riddled with ambiguity.[65] Further, this goal is neither reflective of the objectives of antitrust authorities around the world, nor is it reflective of the objective of U.S. antitrust throughout the history of the Sherman Act. The goals of antitrust are fluid. And many scholars, commentators, and lawmakers are seeking to re-define these goals in the current debate about antitrust.[66]

The use of vague standards in antitrust law permits decision makers the flexibility and discretion to pursue a variety of different and possibly competing objectives, sometimes on an *ad hoc* basis. In our view, the biggest hurdle to the implementation of computational merger review is the inability of human lawmakers to agree on what the law is designed to do.

Predictive technologies solve specific prediction problems. Supervised machine learning algorithms or reinforcement algorithms are designed to achieve a clear, specific objective *or* reward specific types of actions. They seek to maximize some objective. Consensus about that objective is therefore necessary for computational merger review. Lawmakers must make an *ex ante* decision about how society balances and prioritizes certain costs and benefits.

Daryl Lim has suggested that "[t]he beauty of AI is that it can reach outcomes humans alone cannot define as 'good' or 'better' as the untrained neural network interrogates itself via the process of trial and error. . . . [W]ith the AI being capable of scouring options to optimize the best rewards."[67] This is no doubt true in certain circumstances. But it has limited application in antitrust if we have not reached a consensus as to which decisions should be rewarded and which should be punished. To put it another way, the process of trial and error only works if we can easily identify what an error is.

If antitrust authorities are not clear about the objectives of antitrust law, computational merger review can only take us so far. In the end, algorithms cannot solve the very human problem of choosing the objective.

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[65] *See* Orbach*, supra* note 14.
[66] *See, e.g.,* a recent bill put forward by the United States Congress that seeks to strengthen antitrust enforcement. Competition and Antitrust Law Enforcement Reform Act of 2021, S.225, 117th Congress § 2(3) (2021) ("competition fosters small business growth, reduces economic inequality, and spurs innovation and job creation"); *see also* Aurelien Portuese, *Beyond Antitrust Populism: Towards Robust Antitrust*, 40 ECON. AFF. 237 (2020) (arguing that "antitrust populism" and the fear of large corporations has been on the rise in the United States, superseding goals of economic efficiency and consumer welfare); Herbert Hovenkamp, *Antitrust's Borderline* (Univ. of Pa., Inst. for Law & Econ. Research Paper, Paper No. 20-44, 2020), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3656702 (discussing the goals that lie within and outside the boundaries of competition law).
[67] Lim, *supra* note 8, at 50.

A – Antitrust authorities around the world seek different objectives

Antitrust authorities around the world vary greatly in the objectives they pursue. As Edward Iacobucci and Michael Trebilcock show in their survey of eight different jurisdictions, maximizing consumer welfare is *not* the main objective for other competition authorities around the world.[68]

Some jurisdictions seek instead to enhance total welfare or overall efficiency. While the United States and Europe place greater emphasis on the welfare of consumers, Australia and New Zealand tend to emphasize total welfare or overall efficiency.[69]

Other competition authorities explicitly try to protect or defend smaller firms. In Canada, for example, competition legislation seeks to "ensure that small and medium-sized enterprises have an equitable opportunity to participate in the Canadian economy."[70] The protection of small and medium-sized enterprises is also one of the key objectives of Japanese competition law.[71]

Fairness and equity also play an important role in competition law.[72] While these values are sometimes seen as complementary to consumer welfare, there are situations where the conflict arises. For example, a fairness goal might favor small shopkeepers over large supermarkets even when those supermarkets can tap into economies of scale and provide lower prices to consumers.[73]

In still other settings, competition laws are used to protect domestic or state-owned businesses or to break up foreign champions. The exception given to export cartels in many countries—including the United States and Canada—reflects these goals.[74] Similarly, in China, one of the objectives listed is to protect the state-owned economy, encouraging the expansion of domestic enterprises and scrutinizing foreign takeovers.[75]

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[68] Edward M. Iacobucci & Michael J. Trebilcock, *Evaluating the Performance of Competition Agencies: The Limits of Assessment Methodologies and Their Policy Implications* in DAMIEN GERARD (ED.), RECONCILING EFFICIENCY AND EQUITY: A GLOBAL CHALLENGE FOR COMPETITION POLICY 327 (2019); *see also* MASSIMO MOTTA, COMPETITION POLICY: THEORY AND PRACTICE (2009), ch. 1.

[69] *See* Mark Berry, *Institutional Design Issues and Policy Challenges: Reflections from Former Chair of the Commerce Commission, Dr Mark Berry*, 51 VICTORIA UNIV. WELLINGTON L. REV. 231 (2020); Christine S. Wilson, Commissioner, Fed. Trade Comm'n, *Welfare Standards Underlying Antitrust Enforcement: What You Measure is What You Get*, Keynote Address at George Mason Law Review 22nd Annual Antitrust Symposium: Antitrust at the Crossroads? (Feb. 15, 2019); Svend Albæk, *Consumer Welfare in EU Competition Policy*, in AIMS AND VALUES IN COMPETITION LAW (Caroline Heide-Jørgensen, Christian Bergqvist, Ulla Neergaard, & Sune Troels Poulsen eds., 2013).

[70] Competition Act, R.S.C., 1985, c. C-34, § 1.1 (Can.).

[71] Iacobucci & Trebilcock, *supra* note 68, at 332-333. More generally, *see* ETSUKO KAMEOKA, COMPETITION LAW AND POLICY IN JAPAN AND THE EU 94 (2014).

[72] *See* Herbert Hovenkamp, *Distributive Justice and the Antitrust Laws,* 51 GEO. WASH. L. REV. 1 (1982)

[73] On the scale effects in services, retail, and wholesale, *see* Chang Tai Hsieh & Esteban Rossi-Hansberg, *The Industrial Revolution in Services*, PRINCETON (May 12, 2021), https://www.princeton.edu/~erossi/IRS.pdf.

[74] 15 U.S.C. §§ 61-68; Competition Act, R.S.C., ch. C-34, § 45(5)

[75] Anti-Monopoly Law of the People's Republic of China, Presidential Order No. 68 (promulgated by the 29th meeting of the Standing Committee of the 10th National People's Congress of the People's Republic of China, August 30, 2007, effective August 1, 2008).

In South Africa, competition law contains an “extensive and ambitious” list of objectives, designed in part to redress the inequities of the country’s history.[76] For example, South African competition law seeks to promote “participation of all citizens in the economy” and “the fair distribution of ownership and control of markets among different racial groups,” as well as to “balanc[e] the interests of workers, owners, and consumers.”[77]

In the European Union, a key objective has been the promotion of market integration and the freedom of movement of goods, services, capital, and people within the Union.[78] And in Germany in the 1920s, the objectives of competition law even included fighting inflation.[79]

All this is to say that there are many *potential* objectives for antitrust law. Indeed, many in the United States have argued for a broader conception of what antitrust law is and what it should do. Some of these reform advocates have argued that courts, legislatures, and antitrust authorities should embrace broader objectives such as addressing inequality, increasing employment, increasing wages, and mitigating adverse effects on the environment.[80]

B – “Maximizing consumer welfare” is not a clear objective

In the United States, it is commonly assumed that maximization of consumer welfare is the objective—or at least the stated objective—of antitrust law. This was not, however, always the case. In 1890, Senator John Sherman of Ohio stated the following when outlining the purpose of the antitrust act that bears his name: “If we will not endure a king as a political power, we should not endure a king over the production, transportation, and sale of any of the necessaries of life.”[81]

But even if we assumed that “maximizing consumer welfare” is the objective of the law, questions remain about how that can be translated into a well-defined algorithmic objective. Barak Orbach has noted that the consumer welfare standard in antitrust law is “confused and debated” and scholars “hold various views about the desirable interpretations of the standard, and they selectively use judicial statements to substantiate opposite views.”[82] Joseph Brodley noted that efficiency and consumer welfare became dominant terms of antitrust discourse “without any clear consensus as to what they actually mean.”[83]

When Robert Bork argued in his highly influential book, *The Antitrust Paradox,* that the sole normative objective of antitrust was to maximize consumer welfare,[84]

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[76] Competition Act 89 of 1998, pmbl (S. Afr.).
[77] Iacobucci & Trebilcock, supra note 69, at 333.
[78] *Id.* at 332.
[79] OECD, GERMANY—THE ROLE OF COMPETITION POLICY IN REGULATORY REFORM (2003), https://www.oecd.org/germany/33841373.pdf.
[80] *See supra* notes 12-13.
[81] John Sherman, Speech of Hon. John Sherman, of Ohio, Delivered in the Senate of the United States (Mar. 21, 1890).
[82] Orbach, supra note 14, at 133.
[83] Joseph F. Brodley, *The Economic Goals of Antitrust: Efficiency, Consumer Welfare, And Technological Progress*, 62 N.Y.U. L. REV. 1020, 1020 (1987).
[84] ROBERT H. BORK, THE ANTITRUST PARADOX: A POLICY AT WAR WITH ITSELF 7 (1978) (“[T]he only legitimate goal of antitrust is the maximization of consumer welfare.”); *see also* Daniel A. Crane, *The*

he was not actually speaking of consumer surplus in the classic economic sense. Rather, Bork was referring to static efficiency more generally, the maximization of total surplus.[85] While maximizing consumer surplus and maximizing total surplus may often be achieved using the same means, that is not always true. To take one extreme example, perfect price discrimination maximizes total surplus but minimizes consumer surplus.

The differences between maximizing consumer welfare and maximizing total welfare have created tensions in the application of merger law in Canada. Under section 96 of the Canadian Competition Act, anticompetitive mergers that are likely to substantially lessen or prevent competition can still proceed if the gains in efficiency brought about by the merger outweigh and offset the likely anticompetitive effects.[86] There have been vociferous disagreements between the Canadian Competition Tribunal and federal courts about which objective to apply in assessing the efficiencies defence.[87] Ultimately, a "balancing weights" approach has prevailed.[88] The Tribunal may elect to put more weight on consumer surplus than producer surplus. The Tribunal then engages in a value judgment as to whether this weighting is *reasonable* given the income disparity between the consumers of the products and the shareholders of the merging firms. Such a vague standard is not easily translated into an *ex ante* objective.

Returning to the United States, some have suggested that consumer welfare should simply focus on prices. The lower the price, the greater the consumer welfare. According to this view, the objective should be to minimize prices paid by consumers. But low prices may not align with consumer welfare. Low prices for "bads" or status goods, for example, may be inimical to welfare.[89] But even putting aside these conflicts, the goal of lower prices may still be ambiguous for other reasons.

First, which consumers should we be concerned with? Focusing on the prices *paid by the ultimate consumers* of the products of merging companies could be a poor proxy for the economic harms created by mergers. The merger between Facebook and Instagram is frequently offered as an example of a merger that should have been prevented by the agencies.[90] But the nominal dollar price paid by consumers of Facebook and Instagram to this day remains at zero. The prices of digital advertising on these platforms would clearly provide a more accurate picture of the

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Tempting of Antitrust: Robert Bork and the Goals of Antitrust Policy, 79 ANTITRUST L.J. 835, 847 (2014) ("Bork's big move [was] his rejection of alternatives to efficiency or consumer welfare-oriented theories of antitrust enforcement.").

[85] *See* BORK, *supra* note 85, at 110 ("Those who continue to buy after a monopoly is formed pay more for the same output, and that shifts income from them to the monopoly and its owners, who are also consumers. This is not dead-weight loss due to restriction of output but merely a shift in income between two classes of consumers. The consumer welfare model, which views consumers as a collectivity, does not take this income effect into account."); see also Orbach, *supra* note 12.

[86] Competition Act, R.S.C., ch. C-34, § 96.

[87] *See* Canada (Comm'r of Competition) v. Superior Propane Inc., [2003] 3 F. C. 529 (Can. F.C.A.).

[88] Tervita Corp. v. Canada (Comm'r of Competition), [2015] 1 S.C.R. 161 (Can.), ¶¶ 96-101.

[89] *See* Orbach, *supra* note 14.

[90] *See* Chris Mills Rodrigo & Rebecca Klar, 46 *States and FTC File Antitrust Lawsuits Against Facebook*, THE HILL (Dec. 9, 2020), https://thehill.com/policy/technology/529504-state-ags-ftc-sue-facebook-alleging-anti-competitive-practices; Tim Wu, *The Case for Breaking Up Facebook and Instagram*, WASH. POST (Sept. 28, 2018), https://www.washingtonpost.com/outlook/2018/09/28/case-breaking-up-facebook-instagram/.

competition harms. But a balancing exercise may be required in two-sided markets when some consumers benefit from a merger and some consumers are harmed.

Second, what specifically does "price" mean? If, as some have argued, the "price" paid by consumers includes aspects of quality, service, and privacy harms, then arriving at a way to maximize consumer welfare becomes trickier. Even assuming privacy harms are measurable, one must still make difficult decisions about balance. If a merger results in lower dollar prices but greater privacy harms, how does one pre-emptively code the balance inherent in this trade-off in order for the automated system to make a call?

Third, one must balance predictions about likely short-term and long-term effects. An objective that seeks to maximize consumer welfare in the short run may have deleterious effects on consumer welfare in the long run. Static efficiency may come at the expense of dynamic efficiency.[91] A merger that creates synergies in research and development may generate innovations across a variety of dimensions. The merger may raise prices today while providing the benefits of innovation tomorrow.[92] Further, when balancing these effects, one must account for the greater uncertainty of long-term predictions. And so balancing short-term costs against long-term benefits requires agencies to weigh the costs of uncertainty and delay.

The use of micro-directives in merger review will require the agencies to change the way they approach these various these various considerations. In short, the enforcement of vague standards (*substantially lessen competition*) seeking to achieve vague objectives (*maximize consumer welfare*) has allowed antitrust agencies to kick the proverbial can down the road. Currently, no one has to state the law's goals with any specificity. Nor do the agencies have to pursue those goals with any consistency. This will have to change. Creating a computational merger review system will require the agencies and legislatures to be explicit about and commit to the law's objectives up front.

These challenges to computational merger review may also provide a broader unsettling revelation about antitrust law. If the data reveal that the merger review process lacks a clear purpose and has been enforced in pursuit of varying and conflicting objectives, that raises doubts about its legitimacy. This problem lurks in many corners of the law and should not come as a surprise to most legal scholars. But the question remains whether we will tolerate such ad hoc discretion and inconsistency once the data have exposed their full scope.

[91] Dynamic efficiency is often seen as the driving force of long-run economic growth. Robert M. Solow, *Technical Change and the Aggregate Production Function*, 39 REV. ECON. & STAT. 312 (1957); *see also* J. Gregory Sidak & David J. Teece, *Dynamic Competition in Antitrust Law,* 5 J. COMPETITION L. & ECON. 581 (2009).
[92] *See* Richard J. Gilbert, *Competition and Innovation*, *in* A.B.A. HANDBOOK ON ANTITRUST AND COMPETITION 21–24 (2010) (noting that evidence on the relationship between market concentration and innovation is mixed); Sidak & Teece, *supra* note 92, at 587–93.

V. Conclusion

In recent years, antitrust commentators and scholars have argued that merger law in the United States is under enforced.[93] We agree. But merger law in the United States is also over enforced. We argue that the problem lies in the current system of merger notification and review. The coarse threshold rules used in notification are both under-inclusive (allowing anticompetitive mergers to fly under the radar) and over-inclusive (requiring firms to notify agencies and undergo review when there is little or no anticompetitive concern.) And the vague standards used in the substantive test create uncertainty and costs, both to the transacting parties and to the agencies.

In this paper, we have examined the promise of computational law to remedy these flaws. There is much to be excited about in the use of micro-directives in this context. We suggest that advancements in prediction technology can better calibrate merger review and reduce the burden of resource-constrained antitrust agencies while providing useful notice and clarity to the transacting parties. The potential for machine learning to improve the administration of merger law and reduce its costs is enormous.

But the technology will also expose a very human problem with the law. Identifying a precise objective is essential to the creation of micro-directives. For antitrust law, such objective is difficult to locate. The oft-stated purpose of *maximizing consumer welfare* lacks consistent meaning. And antitrust law is often used as a tool to address various other goals. This diminishes our ability to define clear objectives for an algorithm to optimize. The biggest challenge to the effective implementation of computational merger review is thus not the adequacy of technology, nor is it the availability of data. Rather, the real challenge is determining what, *exactly,* we want the law to achieve.

[93] *See* AMY KLOBUCHAR, ANTITRUST: TAKING ON MONOPOLY POWER FROM THE GILDED AGE TO THE DIGITAL AGE (2021); TIM WU, THE CURSE OF BIG-NESS: ANTITRUST IN THE NEW GILDED AGE, 121-124 (2018); Kwoka, *supra* note 34; MLP, *supra* note 7; Lim, *supra* note 8.