ALGORITHMIC CONSUMERS

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Comments most welcome!

INTRODUCTION

Your automated car makes independent decisions on where to purchase fuel, when to drive itself to a service station, from whom to order a spare part, or whether to rent itself out to other passengers, all

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without even once consulting with you. Another application synchronizes health-related data from sensors placed on your pet with data from sensors placed in its food bag, and data regarding pets' seasonal illnesses. Whenever the food is about to run out, the application automatically seeks the best deal and orders pet food of a kind which fits your pet's needs.

Science fiction? No longer. The next generation of e-commerce, researchers say, will be conducted by digital agents, based on algorithms that will not only make purchase recommendations, but will also predict what we want, make purchase decisions, negotiate and execute the transaction for the consumers, and even automatically form coalitions of buyers to enjoy better terms and conditions, thereby bypassing human decision-making. We call these digital assistants "algorithmic consumers."[1]

This is not a huge technological leap. The future is already here. In some industries, such as stock trading, algorithms already automatically translate their results into buying decisions.[2] Another example involves the IBM concept of ADEPT, the acronym for Autonomous Decentralized Peer-to-Peer Telemetry which was revealed in 2015, according to which "things" will automatically communicate with each other to make decisions. To exemplify its application, Samsung and IBM developed the W9000 washing-machine, programmed to order a detergent directly from retailers,

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[1] *See, e.g.*, Minghua He et al., *On Agent-Mediated Electronic Commerce*, 15 IEEE TRANSACTIONS ON KNOWLEDGE & DATA ENGINEERING 985, 985–90 (2003); Don Peppers, *The Consumer of the Future Will Be an Algorithm*, LINKED-IN (July 8, 2013), https://www.linkedin.com/pulse/20130708113252-17102372-the-consumer-of-the-future-will-be-an-algorithm; CHRISTOPHER STEINER, AUTOMATE THIS: HOW ALGORITHMS CAME TO RULE OUR WORLD (2012); Theo Kanter, *Ambient Intelligence*, YOUTUBE (Fe. 3, 2016), https://www.youtube.com/watch?v=1Ubj2kIiKMw.

[2] A relatively early example involves two MIT Media Lab projects that date back to 2000-2002. Impulse and MARI were applications in which a shopper could set the preferences for product types, price and terms such as warranty and manufacturer's reputation. The system negotiated with potential sellers and alerted the shopper if a deal was agreed, subject to the buyer's confirmation. S. Keegan et al., *Easishop: Ambient Intelligence Assists Everyday Shopping*, 178 INFO. SCI. 588, 589–90 (2008); Gaurav Tewari et al., *Personalized Location-Based Brokering Using an Agent-Based Intermediary Architecture*, 34 DECISION SUPPORT SYS. 127, 127–30 (2003).

making autonomous orders and payments, while updating the owner through the smartphone.[3] In addition, various types of intelligent personal assistants, such as Google Now and Apple's Siri, already perform tasks for individual users, based on users' input (such as the user's schedule) and a variety of online sources (such as weather or traffic conditions, or stock prices). Google's new messaging application, Allo, even suggests responses to messages people send to us. Google's vision is that "humans do less thinking when it comes to the small decisions that make up daily life."[4] It is envisaged that algorithmic consumers will become the rule rather than the exception with regard to an exponentially increasing number of transactions.

Algorithmic consumers have the potential to change dramatically the way we conduct business, as well as the competitive dynamics in the market. Using algorithmic consumers *changes the role of human consumers*. Consumers in this ecosystem do not make purchase decisions directly, but consume through algorithms, thereby minimizing the direct role they play in each purchase decision.

The use of algorithmic consumers also *affects market demand and trade conditions*. This results from the fact that algorithmic consumers can significantly reduce search and transaction costs, help consumers overcome biases and make more rational choices, and create or strengthen buyer power. But more importantly, algorithms may construct consumer choice, potentially distancing it from the subjective choice of individual users. Such effects can potentially affect market demand, as well as suppliers' marketing strategies, trade terms and product offers.

These developments raise new and important conceptual and regulatory issues. Indeed, some of the most fundamental conceptions about how markets operate may need to be reevaluated. Will it still

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[3] IBM, ADEPT: An IoT Practitioner Perspective (Draft Copy for Advance Review, Jan. 7, 2015), http://www.scribd.com/doc/252917347/IBM-ADEPT-Practictioner-Perspective-Pre-Publication-Draft-7-Jan-2015; Stan Higgins, *IBM Reveals Proof of Concept for Blockchain-Powered Internet of Things*, COINDESK (Jan. 17, 2015), http://www.coindesk.com/ibm-reveals-proof-concept-blockchain-powered-internet-things.

[4] Danny Yadron, *Google Assistant takes on Amazon and Apple to be the Ultimate Digital Butler*, The Guardian, 18 May, 2016 https://www.theguardian.com/technology/2016/may/18/google-home-assistant-amazon-echo-apple-siri

make sense, for example, to talk about consumer choice, where preferences are defined, predicted and shaped by algorithms? How will market demand and supply be affected? Our regulatory toolbox must be reexamined to ensure that we can deal effectively with market and regulatory failures that arise in this ecosystem. Analyzing such issues is essential and timely, as soon they will become fundamental for e-commerce.[5]

Despite this potentially game-changing technological development, most of the literature on commercial algorithms focuses only on the use of algorithms by suppliers (such as Google, Uber, Amazon, and Target).[6] This literature emphasizes the role of algorithms in collecting and analyzing information about consumers' preferences to better compete for their attention and create more efficient and profitable marketing campaigns.[7] Alternatively, the literature focuses on the potential use of algorithms to more easily facilitate collusion or oligopolistic coordination among suppliers, thereby harming consumers.[8] The focus on consumers is mostly as a resource for the necessary information ("consumers as products"), and as a target for marketing campaigns. The limited literature on the use of algorithms by consumers, has treated them as tools to help consumers compare price and quality, predict price and market trends, make expedient decisions under uncertainty conditions, make better-informed choices, and strengthen competitive pressure overall.[9] This literature disregards the possibility that at a certain point consumers' deference to algorithms may bypass consumers altogether.

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[5] Kevin D. Werbach, *The Song Remains the Same: What Cyberlaw Might Teach the Next Internet Economy*, FLA. L. REV. (forthcoming 2016) (manuscript at 44).

[6] For the seminal article ***see*** Ariel Ezrachi & Maurice E. Stucke, *Artificial Intelligence & Collusion: When Computers Inhibit Competition* (Univ. of Oxford Ctr. for Competition Law & Policy, Working Paper No. CCLP (L) 40, 2015); ARIEL EZRACHI & MAURICE E.STUCKE, VIRTUAL COMPETITION: THE PROMISE AND PERILS OF THE ALGORITHM-DRIVEN ECONOMY (2016)(one chapter focuses on algorithmic consumers).

[7] *See, e.g.,* David Evans, *Attention Rivalry Among Online Platforms,* 9(2) J. COMPETITION L. & ECON. 313 (2013).

[8] Ezrachi and Stucke, *supra* note 8.

[9] *Ibid*.

This article seeks to fill this void. We show that as a result of eminent technological developments, market dynamics may soon change. This, in turn, has significant implications for regulation, which should be adjusted to a reality of consumers making their purchase decisions via algorithms.[10] In particular, we ask whether consumers may benefit from what algorithmic consumers can offer, and what kind of regulation, if at all, is needed in order to ensure this outcome.

We first explore the potential benefits and harms of algorithmic consumers (Part I), and how these advances affect the competitive dynamic in the market (Part II). Such an exploration is essential to articulate the changes introduced by this new technology and to better understand their meaning. We then analyze the implications of such technological advances on regulation, with a special focus on the tools which are necessary to ensure that algorithmic consumers bring about the benefits they offer (Part III). In particular, we identify three regulatory challenges that arise in this regard.

PART I: TECHNOLOGICAL BACKGROUND

How do algorithmic consumers affect consumers' choices? How, if at all, does the algorithm's decisional procedure differ from human purchasing decisions? This Part explores these questions in light of the technological changes that have facilitated a much wider and more sophisticated use of algorithmic consumers.

A. What are Algorithmic Consumers?

Algorithms are structured decision-making processes, based on a set of rules or procedures, such as a decision-making tree, which are designed to automatically supply outcomes based on data input and decisional parameters. In a wide sense, we all use algorithms in our daily lives. For example, when we decide what to eat, we use data inputs (how hungry am I, what is healthy for me, how tasty is it, etc.) and give each of them relative weights in order to reach an outcome that we think might be best for us in accordance with our preferences and decision parameters (e.g., I'll have the salad even though the chocolate cake looks much tastier, because I prefer to be healthy).

[10] *See also* Werbach, *supra* note 5.

Coded algorithms do the same. They use a predetermined decision-tree which gives weights to decision parameters in order to suggest the optimal decision under the circumstances, once given certain data. The decision-tree as well as the decision parameters are set by the algorithm's designer, in a way that seeks to optimize the user's decision. Algorithms then analyze the data inserted into them in accordance with the decision-tree to reach outcomes. In the age of machine learning, in which algorithms can learn from their own analysis of data (deep learning),[11] decisions are no longer confined to predefined preferences. For instance, an algorithm may conclude that the consumer likes to purchase products similar to those bought by his close friends, based on a consumer's past actions, and change the decisional parameters accordingly.

A wide variety of algorithms already assist consumers in their decision-making process in market transactions. At the very basic level, algorithms offer consumers information relevant to their choices. Some simply collect and organize the relevant information provided by suppliers (e.g., Kayak, Expedia and Travelocity offer information on the price and schedules of flights). Others offer information about quality (e.g., rating services such as TripAdvisor and Yelp). More sophisticated algorithms use data analytics to enable price forecasting (e.g., Decide.com). Others narrow down the options for the consumer, based on his characteristics and past revealed preferences, and present only those assumed to be most relevant (e.g., on-line dating services such as OKCupid and Tinder). Some are more sophisticated, suggesting products that the consumer might like, based on his consumption profile (e.g., Google). Such algorithms serve as tools to enhance consumer choice by collecting, aggregating or organizing the relevant data so as to assist the consumer in making an informed decision. But the ultimate decision is still made by the consumer, based on the information provided.

The new generation of algorithms in the service of consumers takes it a step farther, making and executing decisions for the consumer by directly communicating with other systems through the internet. The algorithm automatically identifies the need, searches for

[11] *See, e.g.*, OECD, DATA-DRIVEN INNOVATION FOR GROWTH AND WELL-BEING: INTERIM SYNTHESIS REPORT10 (2014), at 4. For examples of deep learning already used in algorithms *see* Stucke & Ezrachi, *supra* note 8.

an optimal purchase, and executes the transaction. In the algorithmic pet food example, data collected from the pet and the food bags is analyzed by a specialized algorithm to determine the need for additional supply as well as the actual nutrition needs of the particular pet. Decisional parameters to be included in the algorithm may also include real-time data predicting seasonal disease, temporary shortage of certain ingredients, and price changes. Once a choice has been made, based on the data analysis, the algorithm may automatically make an order and arrange for payment and delivery.[12] It can do so with the assistance of on-line software agents (shopping bots).[13]

A recent and provocative example of such a shopping bot involves the Random Darknet Shopper, a shopping bot used in an art project displayed at a gallery in St. Gallen in 2015. For the duration of the exhibition, the artists sent the bot to shop on the Darknet, with a weekly budget of $100 in Bitcoins. The bot chose items and sent them to the artists by mail, without the artists knowing in advance what would be purchased. The orders were displayed in the exhibition.[14]

This rise of algorithmic consumers is facilitated and accelerated by the integrated effect of technological capabilities and consumer demand. Technological advances in data collection, data analytics, big data and artificial intelligence have made algorithms much more convenient and powerful than ever before.[15] Algorithmic consumers' skills in sorting through the relevant data have become more

[12] Jane L. Levere, *When a Robot Books Your Airline Ticket*, N.Y. TIMES, May 31, 2016, at B6.
[13] The intelligence of an agent refers to its ability of performing tasks or actions using relevant information gathered as part of different problem-solving techniques such as influencing, reasoning, and application specific knowledge. Agents could behave autonomously or proactively. *See* Prashant R Nair, *E-Supply Chain Management Using Software Agents*, CSI COMM., July 2013, at 13.
[14] Items purchased by the bot 10 ecstasy pills, a baseball cap-mounted hidden camera system, a fake Louis Vuitton handbag and a fake Hungarian passport. The exhibits were seized by authorities after the exhibition closed. Mike Power, *What Happens When a Software Bot Goes on a Darknet Shopping Spree?*, GUARDIAN, Dec. 5, 2014, https://www.theguardian.com/technology/2014/dec/05/software-bot-darknet-shopping-spree-random-shopper.
[15] Exec. Office of the President, Big Data: A Report on Algorithmic Systems, Opportunity, and Civil Rights (May 2016).

important in light of the exponentially increased volume of data available, [16] which challenges the human cognitive capacity to process the relevant information (otherwise known as “information smog”).[17] The demand for such services is also increasing due to the fact that they enable consumers to free time to handle matters that truly require human discretion (such as work, family, and friends).

Algorithmic consumers may use algorithms at all stages of the transaction. The first involves **data collection**, which is necessary to determine the consumer’s needs and preferences, and identify available purchase options. Data can come directly from the user (e.g., stated preferences the user inserts into the algorithm), or from specialized sensors (e.g., wearable sensors such as Fitbit). Other types of data generally come from external and diverse data sources including suppliers’ websites, social media, video-sharing sites, sensors, and data ancillary to online performance (e.g., transactions, email correspondence, search, reading habits). The relevant data are collected, updated, stored, organized and aggregated, to provide an informed, accurate and comprehensive view of the changing needs and preferences of the consumer as well as his purchase options.

The second step is **data analytics**, in which the algorithm analyzes the relevant data to identify consumer preferences and analyze the purchase options in any given situation. To do so, algorithms may analyze consumers’ personal and subjective data, possibly detaching it from its individualized context. Analysis may also involve comparing consumer’s subjective data with data from other sources to make better predictions about the consumer’s preferences. For example, in the autonomous car example, data analytics may predict that the price of gas might soon rise and buy gas before such a change has taken place.

The third step in the transaction, in which algorithms also play a role, is **decision-making**. The decision of purchase is made in

[16] Yun Wan, *The Evolution of Comparison-Shopping Agents*, *in* AGENT SYSTEMS IN ELECTRONIC BUSINESS 25 (Eldon Y. Li & Soe-Tsyr Yuan eds., (2008).

[17] *See* NIVA ELKIN-KOREN & ELI M. SALZBERGER, LAW, ECONOMICS AND CYBERSPACE: THE EFFECTS OF CYBERSPACE ON THE ECONOMIC ANALYSIS OF LAW 70, 94–96 (2004) (arguing that while the costs of retrieving information in cyberspace may go lower, the cognitive barriers on individual choice are likely to become stronger).

accordance with the decision-tree embedded in their design based on the data analysis they have performed.

The final stage is **performance.** The algorithm may employ and direct shopping bots to perform all stages of the transaction, including negotiating, making the order, signing a contract, paying, and arranging delivery.

Figure 1 below depicts the decision-making process of the algorithmic consumer.

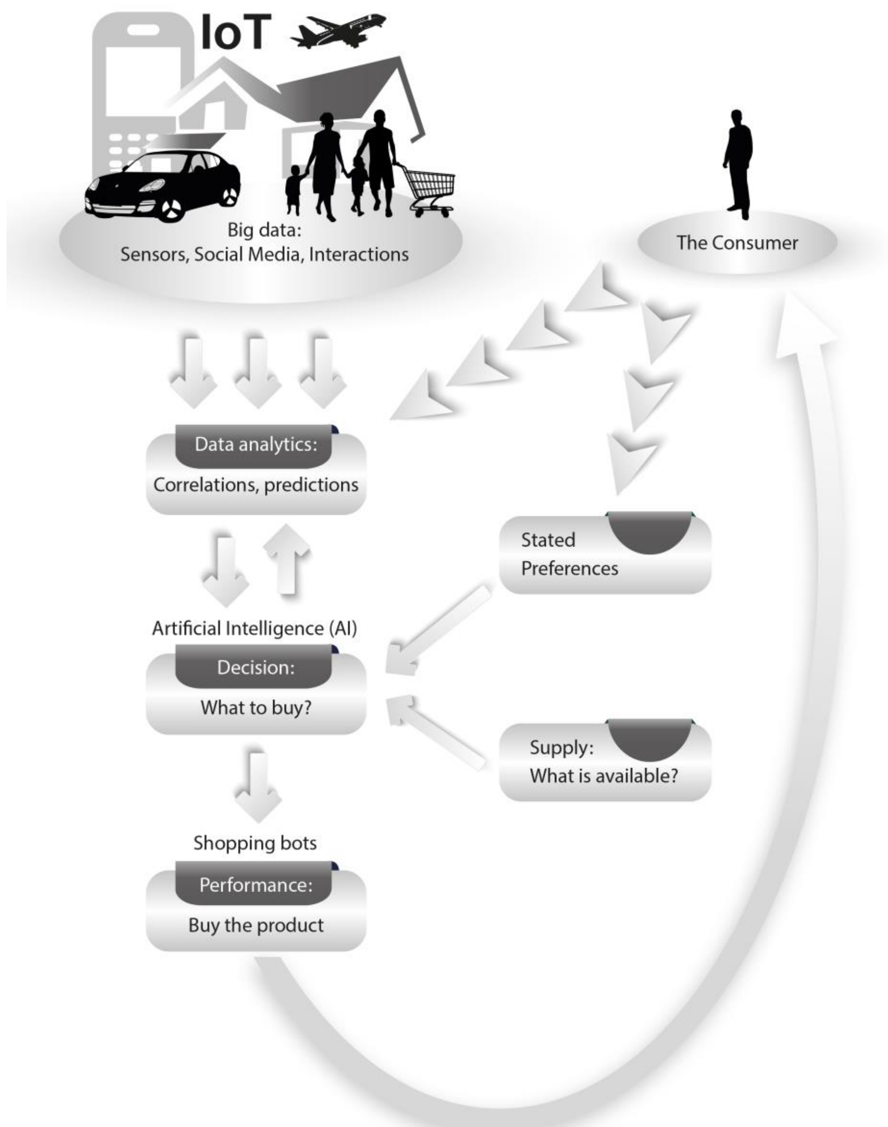

Figure 1: Decision-Making Process of Algorithmic Consumers

None of the foregoing implies that human shopping will completely disappear. In fact, the act of shopping serves some important needs at least for some consumers, such as social interaction and the joy of choosing a specific product (such as jewelry). Nonetheless, even consumers who enjoy shopping may prefer to employ algorithmic consumers with regard to certain products (such as pet food). Some might even prefer to have algorithms make all of their consumption decisions.

Incentives to use algorithmic consumers might be further strengthened by the use of robots and smart devices. Technological developments in robotics enable machines to perform many more actions than ever before in many spheres, including homes and offices. To illustrate, a robot will put the pet food that has arrived on the consumer's doorstep in its storage space, so that the consumer will not be involved in this either. Engineers envisage that as technology develops further, the abilities of personal-use robots will be largely determined by the software rather than the hardware, much like what has happened with smartphones. Smart devices may also ease enforcement in the digital world, thereby further limiting the need for human intervention.[18]

B. The Benefits and Risks of Algorithmic Consumers

Despite the overall similarity in the decision-making process of humans and algorithms, algorithms differ from human decision-makers in important ways. As we shall see, while reducing, and sometimes even overcoming, some consumers' limitations, algorithmic consumers strengthen other types of limitation.[19] These differences are explored below. Identifying these differences is necessary for exploring their potential implications for market dynamic and social welfare, and to design appropriate regulatory responses.

[18] Varian, *supra* note 21, offers an example at 30: "I will sell you a car...." What happens if you stop sending in the monthly payments? Nowadays it's a lot easier just to instruct the vehicular monitoring system not to allow the car to be started and to signal the location where it can be picked up."

[19] Note that some of the characteristics explored below also relate to algorithms that only perform the search function and do not execute the transaction. Observe, however, that the more reliable the searches of algorithms, the stronger the incentives of consumers to rely on them without checking the accuracy of their suggestions and using them as algorithmic consumers. Therefore, the benefits of better search by algorithms are relevant to our analysis.

1. Virtues of Algorithmic Consumers

Consumer choice involves several steps: determining the parameters for the decision, comparing (some) available options based on such parameters, making a choice, transacting with the chosen supplier. As elaborated below, algorithms may reduce the costs and increase the quality of each of these steps.

The most basic advantage of algorithms is that they enable a *speedier decision*. Given any number of decisional parameters and data sources, computers can apply the algorithm much quicker than the human brain can, especially if the decision-tree involves a large number of decision parameters which need to be balanced, or many data inputs that must be analyzed or compared. Assume, for example, that it is worth the consumer's while to spend up to two hours finding the best deal for a certain product. If he has to locate the relevant information and compare it by himself, he might be able to check and compare X on-line offers. An algorithm may be able to explore and compare many more offers (Y>>>>X) in the given time. And even if the algorithm takes longer, the user can use the extra time to do other things. Automatic acceptance of the algorithm's suggestion saves the consumer even more time. This might be especially important in some transactions, such as trading in the stock market or booking a flight soon to depart. Furthermore, many consumers will presumably prefer enjoying free time to spending time on decisions that are not meaningful financially or otherwise.

A second advantage of algorithms involves their *level of sophistication of analysis*. Advances in data collection, storage, synthesis and analysis have ushered in the age of big data, which enables algorithms to integrate numerous variables into the decision-tree. This provides a level of sophistication which usually cannot be achieved by the human mind alone. Not that humans cannot perform these tasks (indeed, the coders of algorithms are human); but it might not be worth their while to do so, given the time and effort involved. An interesting example is Farecast, an algorithm that predicts price changes in flight costs with an accuracy above 70%. It does so by analyzing 175 billion previous airfare data inputs. It is noteworthy that the same data used by suppliers to determine consumers' preferences can be integrated into the algorithmic consumer's decision-tree to make decisions that better serve the consumer.

The level of sophistication is further enhanced by deep learning, the process by which the algorithm learns from its own analysis of the data how to refine and redefine its decision parameters (e.g., determine each consumer's optimal level of risk aversion).[20] Artificial intelligence tools for data mining, online analytical processing, business performance management, benchmarking and predictive analytics also strengthen the algorithm's analytical capabilities. Interestingly, such data analytics tools might identify preferences that consumers themselves are unaware of (e.g., the consumer thinks she prefers healthy food, but she also likes eating chocolate every few weeks). It might also enable the algorithm to identify, but also to predict, a consumer's future preferences (e.g., if she likes to follow certain social trends, the algorithm may identify this behavioral pattern as well as the trends that emerge from the relevant data). Data scientists indeed argue that algorithms can teach us things we don't know about ourselves. In the same vein, Google's chief economist, Hal Varian, recently explained the rationale behind Google's personal algorithmic-based assistant, Google Now, saying that it reflects a vision that "Google ... should know what you want and tell it to you before you ask the question."[21]

Sophistication can also relate to additional parameters in the decision-making process. For example, algorithms may analyze language consumers may not understand and identify legal problems that consumers may overlook.[22] Similarly, algorithms might more easily cope with cultural differences in transacting. Indeed, algorithms can potentially "read" the contractual terms, thereby avoiding at least some contractual limitations that human consumers might fall into, due to time, language, or information constraints.[23]

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[20] *See supra* note 13.
[21] Hal R. Varian, *Beyond Big Data*, 49 BUS. ECON. 27, 28 (2014).
[22] For an example of a methodology and technical tool using natural language processing (NLP) for identify and measure ambiguity in website privacy policies *see* Joel R. Reidenberg, Jaspreet Bhatia, Travis D. Breaux & Thomas B. Norton, *Ambiguity in Privacy Policies and the Impact of Regulation*, 45 J. LEGAL STUD. (forthcoming 2016).
[23] *See* Florencia Marotta-Wurgler, *Does "Notice and Choice" Disclosure Regulation Work? An Empirical Study of Privacy Policies* (Apr. 2015); Yannis Bakos et al., *Does Anyone Read the Fine Print? Testing a Law and Economics Approach to Standard Form Contracts* 43 J. LEGAL STUD. 1, 4 (2014); OMRI BEN-

Interestingly, algorithms need not apply only to one product or group of products, but might help consumers make parallel decisions with regard to a large number of products (mega decision-makers); they can choose among them in keeping with given preferences and a given budget. Algorithms might even calculate for the consumer the minimal budget needed for a certain lifestyle, thereby affecting consumers' choices with regard to the number of (overtime) work hours.

Thirdly, algorithms can *reduce information and transaction costs*. This can occur in any stage of the decision-making process. Let us illustrate this with first stage of this process: determining the parameters for the decision. Many tools exist to aid this stage. For example, the algorithm can offer each consumer a menu of decision parameters to choose from. But more importantly, as noted above algorithms can autonomously define the decision parameters for each consumer, based on her preferences manifested through her actions. Such technology has already been used by some online retailers such as Amazon, which makes marketing suggestions based on past purchases and purchases by other customers with similar profiles. The dating site OKCupid refines consumer choices based on past decisions of dating mates, and Pandora refines its selection of songs for each consumer based on his past preferences (a process called "self-customization"). The algorithm need not know consumers' precise preferences, but sometimes data regarding relative choices are sufficient (e.g., A is preferred to B, B is preferred to C and thus A is preferred to C). These techniques reduce informational costs.

Costs can be further reduced if a similar search is performed for more than one consumer (economies of scale). Such searches need not be simultaneous, since the algorithm can possibly cache the results for future use. Also, the algorithm's capacity to perform its task is limited only by technology; it is never tired, stressed, or sick.

Fourthly, algorithms can *avoid consumer biases*. As numerous studies have shown, humans suffer from biases which lead to non-optimal decisions. We are often swayed by non-relevant factors such as the color of the packaging, or the newest information we have just

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SHAHAR & CARL E. SCHNEIDER, MORE THAN YOU WANTED TO KNOW: THE FAILURE OF MANDATED DISCLOSURE (2014).

heard. Indeed, human choice is often constructed ad hoc during the process of choice and is shaped by context-specific factors.[24] These factors need not affect algorithm choices (unless, of course, we choose to include them in the decision-tree). Algorithms can also avoid biases based on routine (e.g., I always buy this kind of detergent without checking whether other alternatives better meet my needs).

Similarly, algorithms may *overcome manipulative marketing techniques*, which play on people's insecurities, frailties, unconscious fears or desires to affect their thinking, emotions and behavior.[25] To illustrate, an algorithmic consumer will not buy the chocolate stacked near the cashier just because I cannot fight the temptation because I am feeling hungry. Nor will it be subject to subliminal stimulation.[26] Furthermore, it will not be subject to at least some elements of what some call the "new mind control", in which social media and websites manipulate the decisions we make. This is not to say, of course, that algorithms might not be subject to new forms of manipulation, some of which could be avoided by a human purchasers.[27]

Furthermore, the ability to automatically translate the algorithm's choice into a positive action may generate some *positive psychological effects*. For one, the fact that consumers do not need to engage in some otherwise burdensome decisions may increase their level of happiness. Finally, the fact that the algorithm operates automatically can increase the use of online options by consumers who fear or do not know how to take advantage of online purchase opportunities; it thereby *increases equality among consumers*.

[24] *See, e.g.*, THE CONSTRUCTION OF PREFERENCE (Sarah Lichtenstein & Paul Slovic eds., 2006). For a specific example of a bias and how it affects competition and welfare *see* Michal S. Gal & Daniel L. Rubinfeld, *The Hidden Costs of Free Goods: Implications for Antitrust Enforcement*, 80 ANTITRUST L.J. 521 (2016).
[25] Robert Epstein, *The New Mind Control*, AEON (Feb. 18, 2016), https://aeon.co/essays/how-the-internet-flips-elections-and-alters-our-thoughts
[26] *Ibid*.
[27] See infra at 19.

2. New Harms and Risks

Algorithmic consumers might also generate new harms and risks. One major implication of using algorithmic consumers is the *reduction of the autonomy* of consumers. The new generation of algorithms distances consumers from actual purchase choices. While the consumer chooses the algorithm, the algorithm selects the product, so the consumer is one-step-removed from the consumption decision. Furthermore, the consumer (voluntarily) loses the ability to affect the final purchase decision, beyond determining which algorithm to use and possibly selecting which decision parameters to apply.[28]

One may contend that the consumer is exercising his autonomy at a higher level, by choosing which algorithm to use. Moreover, algorithms can be designed to allow the consumer to intervene at any step of the process, from changing the decision parameters (e.g., color of package does matter) to potentially declining the algorithm's suggestion. Yet much depends on the algorithm's transparency level to the consumer, which might be a "black box", especially if big data analysis is applied to shape the algorithmic choice or when the decision-making process involves complex trade-offs. The consumer's motivation and ability to check and verify that the algorithm's decision best promotes his preferences may also be low.[29] It is envisaged that in most cases consumers will generally undergo a pattern of conduct quite similar to that of online contracts: accepting the algorithmic choice as default, without delving into the details and checking whether the optimal choice was made.[30]

A related limitation involves *consumer choice*. The algorithmic choice may not always accurately reflect consumers' preferences. To establish the significance of this welfare challenge, we offer some examples of constructed consumer choices that do not reflect their true preferences. One reason is embedded limitations. For instance, algorithms might not (as of yet) be able to recognize and relate to certain nuances that humans intuitively understand. While such

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[28] Researchers argue that some consumers prefer to be given the responsibility to initiate a transaction. Keegan et al., *supra* note 2, at 592–93.

[29] Interestingly, other algorithms might also be created to perform this task.

[30] BEN-SHAHAR & SCHNEIDER, *supra* note 22.

nuances might not be important in many transactions, they could be essential in others. Accordingly, most of us would probably not want an algorithm to automatically choose our partner in business or in life.

Alternatively, the algorithmic decision might be based on incorrect assumptions embedded in the code by the designer (e.g., one's preference for a certain type of ice cream last week implies the same preference this week); or it may arise from the algorithm's data analysis (e.g., incorrect consumer profiling). As suggested by Barocas, Hood, and Ziewitz, "algorithms embody a profound deference to precedent" since they draw on past behavior to predict future preferences. Consequently, demand as set by the algorithmic consumer might be, at least to some extent, more self-perpetuating and path-dependent than human-based demand would otherwise be.[31]

This vulnerability to biases and errors embedded in the code, or drawn from the data, is not easily overcome. If the consumer is not aware of such assumptions, he might not be aware of some other choices he has forgone. This type of failure might be difficult to fix, as the consumer does not know what he does not know. Consumers may find it increasingly difficult to exercise oversight over sophisticated opaque systems, and might not find it worthy to exercise oversight. As algorithms become more complicated, even the coders might not completely understand the algorithm's decisional parameters.[32]

Another type of potential harm created by algorithmic consumers focuses on the increased *vulnerability of the consumer* to certain harms. One major concern is vulnerability to the risks associated with the digital world such as harm to privacy and the risks of cyber security. Algorithmic consumer systems are likely to collect, record and aggregate immense volumes of personal data. The logic of

[31] Solon Barocas, Sophie Hood & Malte Ziewitz, Governing Algorithms: A Provocation Piece, Paper presented at the Governing Algorithms Conference, New York University (May 16–17, 2014), http://governingalgorithms.org/resources/provocation-piece.

[32] Facebook provides an interesting example: it did not easily find how to change its own newsfeed because so many coders were involved in the creation of its algorithm. Bernhard Rieder, *Studying Facebook via Data Extraction: The Netvizz Application*, *in* PROCEEDINGS OF THE 5TH ANNUAL ACM WEB SCIENCE CONFERENCE 346 (2013).

accumulation requires that all online activities be recorded and analyzed, to optimize the algorithm and improve its outcomes.[33] Security failures may allow access of unauthorized parties to private data, which may then be used without consumers' consent.

Additional concerns also abound, including *manipulation and control of consumers' choices* by the algorithm's designer or owner. So far we have assumed that the algorithm has only the consumer's best interests at heart. But at least in some instances algorithms might be manipulated in ways which do not necessarily foster the consumer's welfare. As recently demonstrated by Facebook in a controversial experiment on contagious emotions, algorithms may also shape the way we feel.[34] When human judgment is replaced by non-transparent codes, consumers are more hard pressed to protect themselves against such manipulation, due to their inability to understand, decipher and challenge algorithms.

Algorithmic consumers may also carry some potentially *negative psychological implications*. Would consumers necessarily be happier in a world in which most decisions were made for them by machines? How would one feel if one was not aware of or did not understand all the parameters that led to a purchasing decision made on one's behalf? And what would consumers do with their spare time? How would the loss of the social interactions that are often a by-product of shopping affect them? Such matters are beyond our expertise, but our intuition suggests that the effect on wellbeing might not all be positive, even if our lives were more efficient and the "correct" decisions were made.

Finally, algorithms can accelerate economic and political inequality: "[t]hose who own the robots and the tech are becoming the new landlord[s]."[35]

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[33] Shoshana Zuboff, *Big Other: Surveillance Capitalism and the Prospects of an Information Civilization*, 30 J. INFO. TECH. 75 (2015).

[34] Jonathan Zittrain, *Facebook Could Decide an Election Without Anyone Ever Finding Out*, NEW REPUBLIC, June 2, 2014, https://newrepublic.com/article/117878.

[35] Izabella Kaminska, *Time to Take Basic Income Seriously?*, FT ALPHAVILLE (June 17, 2013), http://ftalphaville.ft.com/2013/06/17/1536022.

PART II: EFFECT ON MARKET DYNAMICS

The above analysis demonstrated that algorithmic consumers create a host of intriguing effects, many of which hold promise to benefit consumers. In this Part we explore the market dynamics created by algorithmic consumers- the causal links among algorithms, competition, market players, and social welfare- in order in determine whether we can rely on the market to bring about the potential benefits and limit the harms. The analysis will also assist us in locating market and regulatory failures, an essential prerequisite for regulatory policy, and which is the focus of the next Part.

A. Effects on Consumers

One of the most important effects of algorithmic consumers on market dynamics is their ability to significantly *alter consumer demand*, compared to human choices. A foundational question is how these changes in the demand curve affect consumer welfare. The most basic effect of algorithmic consumers is a *reduction in cost and/or possibly an increase in quality* (depending on the preferences set by the consumer) in the products purchased. Such added value is a prerequisite for the use of algorithmic consumers, at least under the assumption that consumers can compare trade terms with and without the use of such algorithms.[36]

The size of these effects depends on the *extent of advantages* enjoyed by consumers. Four cumulative parameters determine this extent. The first is the comparative advantages of algorithms over human-led transactions. The analysis above sought to shed light on this question by highlighting the advantages, as well as the limitations, of algorithmic consumers compared with human transactions. It was shown, for example, that at least with regard to

[36] One might be skeptical about this assumption, for two reasons: First, as explained above, algorithmic consumers have emerged partly as a response to data overload, and the immense number of choices, which are simply impossible to process manually. Second, consumers may find it difficult to fully understand the decision-making process which led to any particular choice, thus might not be able to weigh some of the parameters considered by different algorithms in reaching such choice.

certain types of transactions, an algorithm can execute it in a quicker, less costly, more efficient and more sophisticated manner. The extent of these effects depends, inter alia, on the type of transaction (e.g., whether the consumer has already made similar decisions in the past, or whether the decision involves new and sophisticated parameters), and the type of algorithm and input used (e.g., the sophistication of the algorithmic analysis, and the scope of data it can access and analyze).

The second parameter is the power of the algorithmic consumer vis-à-vis the suppliers of products and of inputs necessary for the successful operation of the algorithm. Generally, the stronger such market power, the greater the benefits from the transaction that can potentially be passed on to the consumer. Strong algorithmic consumers might partly counter the market power of some suppliers. This is especially true with regard to small consumers, who could not otherwise easily protect themselves against suppliers' power. Still, as elaborated below, buyer power can sometimes have negative effects on welfare.

The third parameter is the percentage of the reduced costs or increased value created by the algorithm that is passed on to the consumer. The answer mainly depends on the market power of the algorithm's supplier vis-à-vis the consumer, and is only relevant when the algorithm is not created by the consumer.[37] The stronger the algorithm supplier's market power, the smaller the benefits that will be passed on to the consumer. Such market power rests on several parameters, relating to the height of entry barriers. These may include the number of competing algorithms available in the market, the algorithm's comparative advantages, and the costs of moving to another algorithm. Let us relate to the latter: the personal data accumulated by a specific application on each user may create an important barrier. If the data cannot be used by another platform (due to private or technological limitations on data portability), the cost of switching to another algorithm, and losing the personal

[37] Such control might be manifested in many different ways, one of which is a mandatory requirement that a predetermined percentage of the avoided costs will automatically be transferred to the algorithm's coder or operator, as is done in EXPEDIA (www.expedia.com (last visited Aug 5, 2016)) or BOOKING.COM (www.booking.com (last visited Aug. 5, 2016)).

history, might be prohibitively high. In fact, access to rich, fresh, diversified and dense data on the particular consumer, as well as to data available on other consumers and supply offers, might be crucial for the success of any particular algorithmic consumer.[38] The more unique the data, and the more essential for making an optimal purchase decision, the stronger the market power of the player who has access to such data. This in turn, implies that competition among algorithms might be at least partially affected by access to data. The ability of the consumer to compare the relative qualities of competing algorithms, as well as the default option he has on his digital platform, also determine the extent of market power. Below we explore some parameters that affect the ability and incentives of algorithmic consumers to pass on the benefits they create to consumers.

B. Effect on Suppliers

How do algorithmic consumers change suppliers' conduct, if at all? A major effect relates to trade terms. Since algorithmic consumers may compare a larger pool of products and their characteristics, suppliers might need to adjust their trade terms to meet increased competition. Furthermore, since contractual terms could be checked and rated by algorithms, suppliers may have stronger incentives to improve the contractual terms they are offering and make them fairer. Some of these changes might also create positive externalities on consumers who do not use algorithms to make choices.

Interestingly, the rise of algorithmic consumers will most likely also create new types of data that are necessary for the decision-process, and that could then be analyzed by the algorithm. One example involves data relevant for assessing the risk-levels posed by different websites. Even today, algorithms can be coded to check parameters referring to the reliability of potential sellers (e.g., how long their websites have existed and from where, customer reviews, etc.). By doing so they can analyze a long history of transactions (much like a buyer with an almost infinite memory of his own

[38] For access barriers into big data markets *see, e.g.*, Daniel L. Rubinfeld & Michal S. Gal, Access Barriers to Big Data, Arizona L. Rev. (2017).

transactions as well as other transactions on which he has data). Therefore, online firms will most likely develop better tools to signal their products' level of quality and the reliability of transacting with them, in order to allow algorithms to make more informed decisions

Algorithmic consumers may also affect suppliers' marketing tools: they are likely to invest less in marketing that caters to consumer's biases (such as color of packaging) and invest more in providing information on the product's qualities in ways that can be observed by algorithms. Targeted ads, which are sent to the consumer at times when he is most likely to make a relevant consumption decision (e.g., through his smartphone or smart glasses), will also become less relevant. Finally, since more transactions will be digital, less physical stores and more virtual ones would need to be opened, thereby saving on physical infrastructure and sales personnel. While this trend is already taking place, algorithmic consumers will intensify it. At the same time, suppliers might also seek ways to manipulate the choices made by algorithms in ways that exploit their shortcomings such as blind spots and inefficient decisional parameters. This may lead to a technological race between consumers and suppliers, each bent on developing systems which are able to identify the other's shortcomings while fixing its own blind spots.

How will these changes affect the ease of entry of new suppliers which could, in turn, increase competition? The answer is manifold. On the one hand, path dependency in algorithmic consumer systems (heavy reliance on the trajectory of past purchasing decisions), as well as suppliers' reliability based on past transactions, might give preference to established suppliers. On the other hand, new suppliers might be able to enter the market more easily if reputation and past transactions, as well as the existence of physical infrastructure, are given lesser weight than parameters such as price and quality.[39] In addition, transparency of a widely used algorithm's decision parameters might make it easier for new suppliers to assess how

[39] The literature on discrimination emphasizes that one of the benefits of big data (which is an essential input into algorithms-as-consumers), is that it opens up opportunities for parts of the population which were otherwise categorized as risky. An analogus effect can occur with regard to new suppliers.

much they need to invest in higher quality or lower prices in order to enter profitably, thereby reducing uncertainty and increasing entry.

A related, more subtle yet important, effect on entry and expansion decisions of suppliers involves biases. As long as some level of economic irrationality was expected from consumer choices, some suppliers could make what otherwise seemed irrational entry decisions, and still succeed. But once consumer choices become automated, irrational choices by consumers cannot be relied on. This in turn will affect the type of suppliers that will enter or expand in the market. As Avishalom Tor argues, the welfare effects of such a change are not straightforward; it might even have negative effects on dynamic efficiency, if important inventions are not based on rational decisions of investment and entry.[40]

Another interesting twist on market dynamics is algorithmic consumers that include decisional parameters designed to overcome or at least reduce some market failures in the long run. Algorithms are sufficiently flexible to include considerations such as collective action problems, long-run effects on market structure that might harm consumers, and even environmental considerations. For example, an algorithm might be able to recognize below-cost predatory pricing which will harm market dynamics in the long-run and prevent buying from the monopolistic supplier, even though the price offered is the lowest available. Or it might always buy some portion of its goods from at least one new source, to strengthen incentives for new suppliers to enter the market. Of course, including such decisional parameters requires more sophisticated modeling and analysis of market conditions and their effect on welfare, but given the advances in economics and in data science, they are becoming easier. This, in turn, might significantly affect market dynamics as it might overcome market failures without the need for regulatory intervention.

C. Effect of Algorithmic Interactions

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[40] *See, e.g.*, Avishalom Tor, *Boundedly Rational Entrepreneurs and Antitrust, in* ENTREPRENEURSHIP AND ANTITRUST (forthcoming, 2017).

So far we have focused on how suppliers react to algorithmic consumers, without surveying the methods through which they make their offers. Let us now add another factor to the analysis: suppliers operating through decisional algorithms—a practice already commonplace in many industries.[41] A well-known example is Uber's surge pricing algorithm, which sets the price for the taxi ride at any given time based on the availability of supply relative to demand. This algorithm became famous when in a snowstorm in 2013 an Uber driver, using this algorithm, charged Jessica Seinfeld $415 to drop off her kids at a nearby party. When Uber was criticized, its C.E.O. responded: "We are not setting the price. The market is setting the price. We have algorithms to determine what that market price is."[42] Other examples abound.[43]

So how does the fact that suppliers also often operate through algorithms affect the interaction? The interaction between supplier and consumer algorithms might completely change the dynamics and even the very concept of negotiation. Algorithms will need to be adjusted to a reality of a potentially one-off and extremely quick check and comparison of suppliers' offers. Suppliers will therefore need to design their algorithms to generate the best response to these market conditions. Moreover, the race between the two sides to identify and exploit each other's shortcomings might lead to an "algorithm war," the winner of which will enjoy a larger share of the transactional pie. But most importantly, algorithmic consumers might counteract some of the benefits created by algorithmic suppliers.

D. Increased Buyer Power

Algorithmic consumers can also aggregate consumers into buying groups. This can be done through the creation of a buying platform, operated by one algorithm, or by several algorithmic consumers joining forces. The available technology makes the formation of buying groups easier than ever.

[41] *See, e.g.*, Ezrachi & Stucke, Virtual Competition, *supra* note 8.
[42] Marcus Wohlsen, *Uber Boss Says Surge Pricing Rescues People from the Snow*, WIRED, December 17, 2013.
[43] *See, e.g.*, Ezrachi & Stucke, Virtual Competition, *supra* note 8.

Such algorithmic buying groups may reduce the ability of suppliers to learn about or to use to their advantage *information regarding each user's preferences*, due to the aggregation of the choices of different consumers by one buyer (what might be called anonymization-through-aggregation). Indeed, once consumers are aggregated into sufficiently large consumer groups, suppliers lose the ability to collect information on consumers' individual preferences with regard to the products bought through the group, and discriminate among them based on each consumer's elasticity of demand (e.g., a law professor would be asked to pay much more for a law book than a law student).[44] This in turn might increase consumers' welfare, if suppliers are forced to set a lower price for all. However, in some situations it might also affect welfare negatively, for example, by limiting the ability of some flexible-demand consumers to enjoy lower prices, or by limiting consumers' exposure to personalized offers for products they would otherwise not be aware of but would like to consume.[45] Individually used algorithms might also apply technological strategies to ensure consumers' privacy, thereby creating similar effects.

Algorithmic buying groups can also solve some *collective action problems.* They can also create and strengthen consumers' *buyer power.*[46] The question then arises how increased buyer power affects welfare. What if the increased buyer power simply involves a transfer of wealth to consumers, so that a larger part of the benefits from the trade favor consumers rather than suppliers? This question is not new. It has arisen, inter alia, in the context of purchasing

[44] *See, e.g.*, Samuel B. Hwang & Sungho Kim, *Dynamic Pricing Algorithm for E-Commerce*, *in* ADVANCES IN SYSTEMS, COMPUTING SCIENCES AND SOFTWARE ENGINEERING 149 (Tarek Sobh & Khaled Elleithy eds., 2006).

[45] Exec. Office of the President, Big Data and Differential Pricing (Feb. 2015).

[46] Buyer power indicates the ability of buyers to influence the terms of trade with their suppliers. Joint buying algorithms may create significant market power to consumers, if a significant percentage of buyers makes their purchases through them. Org. for Econ. Co-operation & Dev. [OECD], *Monopsony and Buyer Power* 9, OECD Doc. DAF/COMP(2008)38 (Dec. 17, 2009). A buyer group is established in order to have significant economies of scale and scope, and to take advantage of the effects. Peter C. Carstensen, *Buyer Cartels Versus Buying Groups: Legal Distinctions, Competitive Realities, and Antitrust Policy*, 1 WM. & MARY BUS. L. REV. 1, 9–14 (2010).

cooperatives and joint buying groups.[47] The Federal antitrust enforcement agencies stated that such groups may be assumed to create procompetitive effects, as long as "the purchases account for less than 35% of the total sales of the purchased product or service in the relevant market".[48] We see no reason to exempt algorithmic buying groups from these rules. Yet algorithmic consumers may make buying groups more relevant and powerful than ever, and bypass the limits set by the agencies. Therefore the question of the effect of such power on welfare still remains.[49]

An OECD roundtable identified several potential theories of harm.[50] This is not the place to test their accuracy, but simply to note their acceptance by at least some competition authorities around the world. One theory focuses on reduced incentives of suppliers to invest in productive or dynamic efficiency, if consumers enjoy a large part of the investment.[51] When those joining together are also competitors, another potential harm arises: competitors might use the joint buying algorithm(s) to collude on other aspects of their businesses. In fact, the algorithm can make collusion easier, since it can relatively easily store, compare and analyze the buying requests of each member of the joint buying venture. These potential harms should be balanced by algorithmic consumers' potential ability to counteract the effects of algorithmic suppliers.

Another concern focuses on the ability of algorithmic consumers with market power—unilateral or joint—to limit competition with other algorithmic consumers by engaging in exclusionary conduct.[52] For instance, they can compel their users not to use a competing algorithm (thereby creating downstream foreclosure), or they can coerce suppliers not to supply products to competing algorithms (thereby creating upstream foreclosure). Another example involves price parity—mandating the supplier not to sell to anyone else at

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[47] *See, e.g.*, OECD, *Roundtable on Monopsony and Buyer Power*, OECD Doc. DAF/COMP/WD(2008)79 (Oct. 13, 2008).

[48] *Ibid*, at 5 (citing U.S. DEP'T OF JUSTICE & F.T.C., STATEMENTS OF ANTITRUST ENFORCEMENT POLICY IN HEALTH CARE statement 7 (Aug. 1996)).

[49] Antitrust law is mostly tolerant towards buying groups, even when holding significant share of the input market. Carstensen, *supra* note 46, at 37.

[50] *See Monopsony and Buyer Power*, *supra* note 46, at 9–12.

[51] *Id*.

[52] *Id.*, at 30–32.

lower prices. The incentives of algorithmic consumers to do so are based on the increased benefits from the trade they can enjoy vis-à-vis consumers when competition is limited, as well as the reduced need to invest in making sure their algorithm works best, and keeps up with technological changes, to stay in the game. This in turn reduces the benefits enjoyed by consumers. Motivation to engage in such conduct might exist regardless of whether the consumers are also competitors or end buyers, as long as the algorithm is operated by an external entity.

Algorithmic consumers can also abuse their market power to limit competition among suppliers. Interestingly, exclusion might be achieved covertly: the algorithm might be coded in accordance with certain decision parameters which give little weight to the offers of an otherwise efficient supplier. Note, however, that excluding suppliers might often clash with the interests of algorithmic consumers. Excluding a supplier which might have made the best offer, or at least strengthened competitive pressures on other competitors, might reduce the algorithm's market value. Accordingly, incentives to engage in such exclusionary conduct will generally be low, as market forces will limit their existence. Incentives might change when such exclusion creates market value, for example, when consumers feel strongly about not buying from certain firms (e.g., firms which exploit child labor), and are willing to give up otherwise better offers. Or when the algorithm's operator also competes in the market for the supply of products.[53] End consumers generally have even weaker incentives to engage in conduct which excludes suppliers or algorithmic consumers.

These concerns for the abuse of market power by algorithmic consumers are exacerbated by the high entry barriers into the market for (some) algorithmic consumers, explored in the next section.

E. Barriers to Competition in Digital Markets

[53] This paper is based on the assumption that suppliers, buyers and algorithm operators are separate entities, operating at different levels of the supply chain. Once this assumption is relaxed, additional competitive issues arise. While intriguing, they are beyond the scope of this paper.

So far the analysis has focused on consumers, algorithmic consumers and suppliers, largely disregarding the intermediaries that connect them or firms that provide inputs they need. However, once we expand our point of view accordingly, market dynamics change.

The following discussion mainly addresses two points of control which could critically shape algorithmic consumers' conduct: (1) Access to potential users; and (2) Access to data –the ability to collect and analyze data which is relevant to the transaction, including data on the preferences of a particular consumer. As we shall show below, currently both points of control may exhibit high entry barriers.

Digital markets suffer from a high level of concentration. Currently a handful of digital intermediaries with mega platforms control effective points of access to potential users. These include smart devices (such as iPhone, Kindle), operating systems (such as iOS, Android), application stores (Apple Store and Google Play) and browser entry point (such as Google Search and Facebook). The high level of concentration is largely due to network effects, created when the value for each consumer of using the platform is increased in parallel to the number of others using the system.[54] These network effects may also relate to big data. By converging control of content, access and online distribution channels, large networks enjoy inherent competitive advantages in access to immense volumes of users' personal on-line data.

This situation has several implications for the likelihood of competition in the market for algorithmic consumer applications. Most importantly, currently access to such intermediaries is essential for most suppliers of algorithmic consumers, since they generally need to go through them to reach their users (e.g., through an app store) or to collect the relevant data (e.g., through a search

[54] Nicolai Van Gorp and Olga Batura, *Challenges for Competition Policy in a Digitalised Economy*, IP/A/ECON/2014-12 (July 2015). They are increased by the network effects of big data. *See, e.g.*, Rubinfeld and Gal, *supra* note ?; MAURICE E. STUCKE AND ALLEN P. GRUNES, BIG DATA AND COMPETITION POLICY (2016), ch. 11-13 (big data exhibits several types of network effects: network effects arising from the use of a product by many others, trial-and-error and learning-by-doing network effects, scope of data and spill-over network effects in multi-sided markets).

application). As a result, digital intermediaries may affect which algorithmic consumer would reach potential users, and on which terms.

Alternatively and perhaps more realistically, mega-platforms may attempt to supply and control algorithmic consumers by themselves, given that such algorithms are likely to become consumers' gateway into the digitized world.[55] This is strengthened by the fact that algorithmic consumers can obscure each individual consumer's preferences by aggregating all of them, might limit incentives of platforms whose value depends on such data to grant access to such applications. The more important the access through the intermediary or to the unique data held by it, the more likely that the handful of mega-platforms dominating digital markets will attempt to control it. This, in turn, might further fortify the mega-platform's market power and increase entry barriers into both the mega-platforms' and the algorithmic consumers' markets.[56]

Indeed, the major digital platforms are already racing to develop the best smart shopping assistant.[57] Furthermore, one of the strategies used by some mega-platforms to lure consumers to their applications is to create a multi-task algorithm, which combines many functions, some of which provide additional services such as organizing one's calendar, reminding her of scheduled meetings or to take an umbrella when rain is forecast, and ringing up one's contacts upon the user's request ("Digital Butlers").[58] Algorithms like Siri and Google M already perform many of these tasks, free of charge, and in the near future it is envisaged that they could do many more, and will also

[55] See also Ariel Ezrachi and Maurice E. Stucke, *Is Your Digital Assistant Devious?* http://ssrn.com/abstract=2828117 forthcoming as chapter 21 in ARIEL EZRACHI AND MAURICE E STUCKE, VIRTUAL COMPETITION - THE PROMISE AND PERILS OF THE ALGORITHM DRIVEN ECONOMY (2016).
[56] Ezrachi and Stucke, supra..
[57] *See* Mark Prigg, *Apple Unleashes its AI: 'Super Siri' Will Battle Amazon, Facebook and Google in Smart Assistant Wars*, DAILY MAIL (June 13, 2016), http://www.dailymail.co.uk/sciencetech/article-3639325/Apple-unveil-SuperSiri-Amazon-Google-smart-assistant-wars.html.
[58] This term was coined by Danny Yadron, 'Google Assistant takes on Amazon and Apple to be the ultimate digital butler'; https://www.theguardian.com/technology/2016/may/18/google-home-assistant-amazon-echo-apple-siri

combine purchasing decisions (e.g., the example given by Google: "find my son a Spanish tutor").[59] Accordingly, firms like Google and Apple have evolved from mainly intermediaries in two-sided markets (between advertisers and consumers), to multi-tasking agents, combining a multitude of services, including algorithmic consumers.

This technological tying of services may (partially) mitigate the loss of power resulting from the scenario elaborated below in which digital intermediaries might become less important as a source of big data and of reaching suppliers. It also gives them inherent advantages that create entry barriers into their markets. First, because of their current dominant position over existing platforms, their digital butlers become the default option. This, in turn, creates a large base of users and raises switching costs. Second, the combination of many tasks, including free ones which they already provide (e.g., free maps), which consumers already use, creates an advantage relative to a uni-task algorithm. This advantage is strengthened by a one-stop-shop and the potential interconnectedness of the decisions that these digital butlers offer. Third, the fact that they also serve as digital butlers allows them to collect and accumulate more data on each user, which enables them to create better user profiles, which in turn enables them to act as better algorithmic consumers.[60] Fourth, and relatedly, the fact that such intermediaries currently serve as major gateways to the digital world, enables them to accumulate more data. To the extent that data about other users (as differentiated from data about each user) is important for the algorithmic consumer's functioning, this might further increase entry barriers.[61] Therefore, their roles of algorithmic butlers and consumers reinforce each other and raise the entry barriers to other firms in the market for algorithmic consumers. If so, users might be inclined to have these platforms also perform buying for them.[62]

An interesting question is how this market structure will affect the supply of goods. Data on consumers' actual and predicted

[59] Google's video, in Yadron.
[60] See also Ezrachi and Stucke, paper, "The key is to control as many aspects of our online interface and reap the associated benefits."
[61] For such a claim see Ezrachi and Stucke
[62] It is interesting to note, that relatively similar claims were raised with regard to search engines.

preferences can generate a significant competitive edge to suppliers that would collaborate with the mega-platforms. This is because such suppliers could better predict and cater to consumers' demand. Consequently, control over consumer data may enable platforms using algorithmic consumer systems to leverage their power into the supply of goods. This would actually result in significant power over both demand and supply. Another troubling effect is a situation where the mega platform controls both the consumer algorithms and some suppliers. The risk is that the platform might use algorithmic consumers to shape demand to match their own supply. More subtle effects might also arise: even when the mega-platform does not control suppliers, it might change consumers' choice, if it gives it an advantage in other aspects of its operation.[63]

Based upon these current features of digital markets, Ezrachi and Stucke suggest a pessimistic vision, suggesting an inevitable path that leads to the control of consumer algorithms by the existing intermediaries, which would lead to decisions which will not necessarily made with the consumers' welfare as their main goal.[64]

We do not share this view. Rather, technology is a bit like a phoenix, reinventing itself time and again, sometimes with the assistance of correctly structured regulation. Degrees of power and methods of control may change and introduce more competition. Just like the points of control have historically moved from the individual computer to the internet, the latter might soon lose some of its power due to new technological developments. Most importantly, the internet-of-things (IOT) may change the locus of data which is important for the operations of algorithmic consumers from the internet towards more physical, and possibly less concentrated, locuses (such as smart homes, smart cars, smart appliances, smart clothes). This, in turn, might shift at least some of the power away

[63] For example, if it can experiment with how users react to choices which do not necessarily fit exactly their preferences, but might increase the mega-platform's revenues. See, by way of analogy, the Facebook experiment on how changes in the newsfeed changed its users' emotions. Adam D. I. Kramer, Jamie E. Guillory, and Jeffrey T. Hancock, Experimental evidence of massive-scale emotional contagion through social networks, PNAS Early Review, March 25, 2014, https://cornell.app.box.com/v/fbcontagion.

[64] Ezrachi and Stucke, *supra* note ?.

from the existing internet intermediaries.[65] Firms like Google have already started to expand into markets which provide them with information from physical infrastructures, such as smart home devices and smart cars. This "sensor-control war", however, will not be an easy one for the existing mega-platforms to win, as it is hard to imagine one firm which controls all or most of the sensors embedded in numerous physical sources. Interoperability between data sources (either mandated or market-driven), might also change the points of control.[66] Moreover, where the data necessary to make a decision on behalf of the consumer need not be vast or varied (e.g, what kind of pet food to buy), and the decisional parameters are quite transparent, there may well be a place in the market for the creation of algorithmic consumers which are not operated or controlled by the intermediaries, or at least for more transparency of algorithms' decisions, which in turn would create stronger competition. Finally, technological changes may also reduce barriers to the execution of transactions. Rather than go through search services suppliers, in some instances algorithmic consumers may potentially directly interact with suppliers through the internet.

This does not imply that new technologies or market structures overcome all the limitations to the efficient operation of algorithmic consumers, but it does shed new light on how markets are likely to operate in the future, and potentially opens the door to less concentrated market structures.

To summarize Part II, algorithmic consumers can create positive effects on consumer and social welfare. By increasing competition among suppliers, they are likely to increase allocative, productive and dynamic efficiency, which in turn would lead to lower costs and higher quality products. Moreover, they lower the transaction costs for all involved, thereby further improving social welfare. Nonetheless, some negative effects on social welfare can arise, mostly when algorithmic consumers abuse their market power to create artificial barriers to competition, or when firms leverage their

[65] Niva: cite to your own work and that of Yochai

[66] See Michal S. Gal and Daniel Rubinfeld. "Interoperability and Compatibility of Big Data" (on file with author).

market power in digital markets to affect the market for algorithmic consumers.

PART III: IMPLICATIONS FOR REGULATION

Having identified the advantages and disadvantages of algorithmic consumers relative to human-led transactions, as well as their potential effects on market dynamics and social welfare, this Part focuses on the regulatory challenges that arise from this technological change: does current regulation meet the regulatory challenges raised by algorithmic consumers, or does it miss some important elements and therefore must be adjusted?

The advent of algorithmic consumers raises a host of intriguing challenges in many different aspects of current regulatory tools—for instance, in contract law: can an algorithm act in bad faith? When does the interaction among algorithms constitute a binding contract? Who are the contracting parties to an algorithmic transaction? In tort law: who is responsible for harm created by an algorithm? Or in newer forms of regulation such as privacy and cyber security: should algorithmic consumers be mandated to meet certain regulatory standards with regard to privacy or the level of security they employ?[67] Such challenges, as well as related ones, will surely arise in the brave new world of automated consumer decision-making.

This article focuses on an important piece of the regulatory puzzle: does current regulation ensure that the consumer will receive the benefits algorithmic consumers promise. A major tool is antitrust laws. Antitrust is a foundational regulatory tool: it attempts to ensure that markets work to the benefit of society by preventing or limiting the erection of artificial barriers to competition by private firms. It is based on the assumption that unobstructed competition, which

[67] Additional questions arise, inter alia, in corporate law (e.g., under what circumstances is a corporate agent acting negligently or in bad faith when he does not accept a decision made by an algorithm?); consumer law (e.g., When do manipulations by algorithmic consumers infringe consumer protection standards? What kind of information should the algorithm's supplier provide to the user? What type of actions should be regarded as negotiations?); criminal law (Who purchases an illegal artifact if the consumer gives the algorithm a carte blanche and the algorithms purchases such an artifact without the consumer's specific consent and even without him being aware that such a purchase is possible?).

creates a status quo based on the interaction of supply and demand in the market, will in the long run increase social welfare. Furthermore, where increased competition, protected through antitrust, can avoid or reduce market or regulatory failures, antitrust may negate the need to apply other, more interventionary, regulatory tools. For example, where competition between suppliers of algorithms lowers their incentives to manipulate the algorithm's decisional parameters, consumer protection law might be less important. Finally, in the general absence of other, more specific regulatory tools that pertain to the furtherance of competition in algorithmic markets, antitrust is the main tool which is currently relevant. Accordingly, below we analyze the potential application of antitrust to algorithmic consumers, in order to ensure that consumers indeed can enjoy the benefits they have in store.

Yet antitrust does not eliminate all market and regulatory failures: it often cannot efficiently handle market failures such as information asymmetries, collective action problems and externalities. Accordingly, we also explore how other laws might supplement antitrust in order to ensure that consumers enjoy the benefits algorithmic consumers may bring.

The unique characteristics of algorithmic consumers and the markets in which they operate, elaborated in Parts I and II, create three major challenges to regulation, to ensure that indeed algorithmic consumers increase welfare to the extent possible. These challenges relate to the height of entry barriers which might prevent competition among algorithmic consumers, thereby limiting their benefits. Below we identify and analyze the regulatory challenges.

A. Reducing Barriers to Access to Consumers

Even if a firm possesses the best algorithm, it might still find it difficult to reach consumers. Some barriers are natural, such as first-mover advantages which may create a status-quo bias, and imperfect information of consumers. Some of these can be (partially) solved by the market. For example, product-comparison firms might increase the level of knowledge of consumers regarding the relative qualities of different algorithmic consumers. The law can also assist in lowering such barriers, for example by prohibiting misleading advertisements, or by requiring transparency about some product qualities. In this regard, algorithms are no different from other products, except that it might be more difficult to observe their relative qualities, due to their "black box" features, especially if they make multiple interrelated decisions.

A more significant barrier involves access to consumers through intermediaries. As noted above, currently several large intermediaries control the platforms through which application providers and consumers interact, most importantly smart devices, operating systems, application stores, and browser entry points. Once such entry points are foreclosed or limited to application designers, access to consumers is also limited, and so is their ability to compete effectively. Moreover, intermediaries might then use their market power over access points in order to create their own algorithmic consumers, or to join forces and support one algorithm over another, thereby enjoying part of the profits to be had. As long as algorithmic consumers are an insignificant part of what the intermediary has to offer, such conduct might not create too strong incentives for users to switch to another intermediary. Accordingly, in such instances we cannot rely on market forces to solve this foreclosure problem, at least not in the short run.

Can existing law assist in overcoming such barriers? The answer is a partial yes, dependent on the conditions of the market and the type of conduct that the intermediary is engaged in. The most relevant law is the antitrust prohibition against monopolization or attempted monopolization, which is designed to capture unilateral conduct by a firm with significant market power, which uses this power to erect artificial entry barriers before its competitors.[68] For antitrust liability to arise, the following conditions must be proven: possession of (or attempt to possess) monopoly power; an act of monopolization, which has been defined as "the willful acquisition or maintenance of that power as distinguished from growth or development as a consequence of a superior product, business acumen or historic accident";[69] and the existence of a causal link between the conduct and market power.[70]

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[68] 15 U.S.C. §§ 1, 2 (2014) (respectively). For an overview of antitrust *see, e.g.*, PHILLIP E. AREEDA & HERBERT HOVENKAMP, ANTITRUST LAW (4th ed. 2013); HERBERT HOVENKAMP, FEDERAL ANTITRUST LAW (4th ed., 2011).
[69] United States v. Grinnell Corp., 384 U.S. 563, 570–71 (1966).
[70] *Ibid*.

When these conditions are met, antitrust can be used to mandate the intermediary to stop engaging in anti-competitive conduct. The monopolist might be required to stop discriminating in access terms or stop other exclusionary practices towards some algorithmic consumer suppliers. One doctrine which is worth mentioning is the essential facilities doctrine.[71] While much controversy has arisen with regard to the scope of the doctrine, it is still applicable in some cases.[72] Under the doctrine, when a monopolist controls an input, access to which is essential for other, similarly efficient, firms to compete in a related market, and granting access is feasible and not objective unreasonable, the monopolist is mandated to grant access to its facility on fair and non-discriminatory terms.

Antitrust is, however, a very limited tool for mandating access to intermediaries, for several reasons. First, significant difficulties exist in proving the existence of a monopolistic position, especially in dynamic markets.[73] This implies that antitrust does not capture two main situations in which access might be prevented by an intermediary. The first involves market power in a niche market. Another involves market power that arises from oligopolistic coordination, that is, parallel conduct of several large competitors, which is not based on an illegal agreement among them. To give an example, in might be that Google and Apple both limit access to their online application stores, without a prior agreement. Should it be established that neither enjoys a monopolistic position in the market for application stores, antitrust could not be used to grant access.[74] Second, antitrust generally does not limit the price that can be set by the monopolist in exchange for access. This, in turn, might limit the benefits to be had by the consumer.

In the long-run, however, other platforms may be created that will compete over users and may therefore grant better terms of access to algorithms. This is especially true if multiple types of intermediaries can grant such access, even if they do not compete in the same market (e.g., access through Facebook, rather than through Apple). Yet such access might not be easy, due inter alia to the

[71] cite
[72] Cite.
[73] See, e.g., the case against Google in the US.
[74] See, e.g., Scott Hemphill and Tim Wu, Parallel Conduct

switching costs and inherent benefits created by scale economies, multi-tasking, first mover advantages and default options which characterize many digital markets.

B. Reducing Barriers to Access to Relevant Data

Whenever data is essential for the successful operation of the algorithmic consumer, in order to determine and update the consumer's preferences, access to such data and the tools available for analyzing it affect the level of competition. As we move from stated preferences to predicted preferences based on data analysis and especially deep learning, data's role becomes more important for competition. Indeed all dimensions of big data might contribute to the erection of entry barriers.[75] Scale (Volume) creates network effects of learning-by-doing and trial-and-error; Scope (Variety) may increase the algorithmic consumer's ability to make optimal decisions among several different products by balancing the consumer's preferences for these products (e.g., buy this book and reduce the budget for clothes accordingly). Speed (Velocity) enables a faster reaction of the algorithm to its user's actions and needs. In such situations those controlling the data might enjoy inherent advantages.

Here, again, antitrust can reduce some of barriers, but not all. Most importantly benefits arising from data collection may not arise from the erection of artificial entry barriers, and therefore generally will not be caught by antitrust.[76] Moreover, some remedies (such as granting access to data obtained anti-competitively), might harm other interests such as privacy and require a delicate balance for which antitrust is not necessarily well suited.[77] Accordingly, should access to such data be deemed important for social welfare, other

[75] See, e.g., Rubinfeld and Gal, *supra* note ?; Stucke and Grunes, *supra* note 99, ch. 11-13.
[76] An important question focuses on what should be considered monopolization and what should be considered competition on the merit. See, e.g., MAURICE E. STUCKE AND ALLEN P. GRUNES, BIG DATA AND COMPETITION POLICY, Chapter 18 (2016).
[77] For a similar conclusion see also Stucke and Grunes, *supra* note 93.

regulatory tools might need to be devised, such as rules on data portability.[78]

A related issue regards data interoperability. In order for new competitors to be able to use the data collected by others, it is important that they be able to recognize its patterns and use it. Yet competing firms might not have incentives to create data interoperability. A tough question is whether the law should mandate it. Both horns of the dilemma involve efficiency considerations. On the one hand, mandating standardization of data organization might limit dynamic and productive efficiency of those collecting it in accordance with their own needs. On the other hand, absent interoperability, synergies that could otherwise be created will not be realized, and competition might be limited. In any case, interoperability barriers generally cannot be reached by antitrust as long as they are not the result of artificial entry barriers. Other regulatory tools might then need to be devised to enable it.

C. Exclusionary Conduct Among Algorithms

The above analysis focused on barriers to competition resulting from third parties: access intermediaries and controllers of data. While some algorithmic consumers may serve a dual function, this is not necessarily the case. Below we analyze a third source of entry barriers: exclusionary conduct by algorithmic consumers. To give an example, an algorithmic consumer might enter into exclusive dealings contracts with suppliers, thereby foreclosing access to other algorithmic consumers. Exclusionary conduct by algorithmic consumers can also create artificial entry barriers to suppliers. This might be the case, for example, when the algorithmic consumer makes a decision not to buy from a certain supplier, even if he proposes the best terms. The analysis below generally applies to both cases. Here, in contrast to the two situations analyzed previously, antitrust can play a major role.

A relatively simple case exists when an algorithmic consumer, which enjoys significant market power, engages in exclusionary anti-

[78] For example, the European Data Protection Supervisor regulation includes a right for private data portability, thereby restoring at least some of the power to the consumer.

competitive conduct. Such conduct might then be captured under the monopolization prohibition.

The more interesting case arises when each algorithm, on its own, does not enjoy market power. Yet the existing algorithms engage in parallel conduct which might create anticompetitive effects. While the algorithm is applied separately and independently by each user on his own, the cumulative effects arising from parallel use of the algorithm(s) by many users can sometimes harm competition and welfare.

Algorithms may assist in engaging in parallel conduct. Nobel Prize winner George Stigler pointed to three conditions which must exist for the success of intentional parallel conduct: reaching a status quo that benefits all those engaged in such conduct in the long-run, monitoring deviations from the status quo, and policing such deviations.[79] Algorithms make meeting these conditions easier than ever.[80] First, algorithms can quickly and efficiently observe prices offered by suppliers to other consumers, or remember offers made by suppliers in the past, thereby simplifying reaching a status quo and monitoring. Secondly, they can automatically respond to certain price offers in accordance with predetermined decision parameters, thereby more easily reaching a status quo and policing the conduct. Thirdly, they may create a "credible threat" of policing deviations, especially if decisions are quick and changing the algorithm's decision-tree is not simple (e.g., it has to go back to the coder). Hence algorithms may create more durable parallel conduct. Furthermore, due to these more efficient ways of fulfilling Stigler's three conditions, parallel conduct can be reached even if the algorithmic market is comprised of many small algorithms rather than being highly concentrated.

For antitrust liability to arise from parallel conduct, an "agreement" must be found to exist among those engaged in the anticompetitive conduct. Under established doctrines, parallel conduct emanating from the effect of similar external forces (such as price increase of a major input which affects all competitors alike) or

[79] George J. Stigler, *A Theory of Oligopoly*, 72 J. POL. ECON. 44 (1964).
[80] Salil K. Mehra, *Antitrust and the Robo-Seller: Competition in the Time of Algorithms*, 100 MINN. L. REV. 1323 (2016); Ezrachi & Stucke, *Artificial Intelligence, supra* note 8.

from oligopolistic coordination, does not constitute an "agreement."[81] Oligopolistic coordination is created when each market player makes a unilateral decision which takes into account the reaction curves of other market players, and the result is parallel conduct without a prior agreement.

Let us first explore which types of parallel conduct *among algorithmic consumers* satisfy this condition. In their seminal work Ezrachi and Stucke identify four scenarios.[82] A relatively simple scenario involves the use of algorithms to implement, monitor, police or strengthen an anticompetitive agreement among users or suppliers of algorithms. In such a situation a clear agreement exists.[83]

A more technologically complicated yet legally simple situation arises when the algorithms are purposely coded, by agreement among users or suppliers of algorithms, to enter in the future into an anticompetitive agreement (e.g., boycotting a certain supplier), should such an agreement benefit them. Once again, an agreement clearly exists and the algorithm simply acts as its facilitating device.

A third scenario involves oligopolistic coordination among algorithms, reached without the need for a preliminary agreement among them. Rather, a stable status quo is achieved when each algorithm is coded to make its decisions based on its predictions of the best responses and the dominant strategies of other parties in the market. This leads to parallel conduct without prior agreement, which could be facilitated automatically.[84]

In the fourth scenario ("Automated Agent") the algorithms are designed to achieve a given target such as price reduction. The

[81] *See, e.g.*, ANDREW I. GAVIL ET AL., ANTITRUST LAW IN PERSPECTIVE: CASES, CONCEPTS AND PROBLEMS IN COMPETITION POLICY 267–68 (2d ed. 2008).
[82] *Supra* note 6.
[83] *See also* Ezrachi & Stucke, *Artificial Intelligence*, *supra* note 8; Press Release, U.S. Dep't of Justice, Office of Pub. Affairs, Former E-Commerce Executive Charged with Price Fixing in the Antitrust Division's First Online Marketplace Prosecution (Apr. 6, 2015) (alleging that the sellers "adopted specific pricing algorithms for the sale of certain posters with the goal of coordinating changes to their respective prices and wrote computer code that instructed algorithm-based software to set prices in conformity with this agreement"). Such agreements are illegal regardless of the market power of their parties. *Socony-Vacuum Oil*, *supra* note **Error! Bookmark not defined.**, at 221.
[84] Ezrachi & Stucke, *Artificial Intelligence, supra* note 6, at 16–17.

algorithms determine independently the means to reach that target, through self-learning and feedback collected from the market. Therefore parallel conduct is not the fruit of explicit human design but the outcome of evolution, self-learning and independent machine execution.[85]

Ezrachi and Stucke argue that parallel conduct that results from the Predictable Agent and the Automated Agent scenarios does not constitute an "agreement" for the purpose of antitrust, because it constitutes oligopolistic coordination which is not captured under the law.[86] We would like to offer a different suggestion. One of the exceptions to the rule that exempts oligopolistic coordination from antitrust liability is the existence of "plus factors".[87] These are positive actions, engaged in by market players, which go beyond the market's natural conditions, and allow firms to better achieve parallel conduct. In both cases it can be argued that the algorithm, more especially its design, is such a plus factor. It includes in the decision-tree elements that not only scan the available options and base the consumption decision on their comparison, but also change buyers' decision parameters to include reactions to offers to others, thereby also changing the suppliers' incentives. The fact that, as noted above, algorithms make coordination easier, strengthens this suggestion. Arguably therefore, an "agreement" exists among the suppliers of such algorithms, and possibly also among their users, because the algorithm constitutes a "plus factor". Another "plus factor" may exist if users purposely choose to use the same algorithm, even if it is not

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[85] *Id.*, at 22–25.

[86] Ezrachi & Stucke, *id.*, briefly relate to this possibility at 21, fn.41:

> The benefit of this approach is that it may be easier to prove that the industry agreed to use algorithms (especially in order to ensure their interoperability) and knew that its rival firms' algorithms had similar reward structures than it is to prove an agreement to fix prices. The downsides of this approach are the cost, duration, and unpredictability of a rule of reason case, and the difficulty for the court in weighing the pro-competitive benefits of product developments with the anticompetitive effects.

[87] See, e.g., William E Kovacic,, Robert C. Marshall, Leslie M. Marx, and Halbert L White, *Plus Factors and Agreement in Antitrust Law*, 110 MICHIGAN L. REV. 393 (2011).

the most efficient, but for the parallel conduct it creates. The incentives to do so arise in that using a similar algorithm can contribute to the stabilization of parallel conduct, given that algorithms can more easily predict each other's reactions.[88]

Alternatively, legislators and courts might need to reevaluate the current policy of exempting oligopolistic coordination from the prohibition against anticompetitive agreements. This is because some factors underlying the regulatory decision not to regulate oligopolistic coordination[89]—principally that it does not affect many markets—may no longer be true. Indeed, this justification was based on assumptions of limited human capacity that no longer hold. Once we introduce algorithms. Not only does oligopolistic coordination become more durable, but it may also actually be facilitated in non-oligopolistic markets. The requirement that a prior agreement exist among market players therefore does not fit the algorithmic world. The major problem with this solution is similar to the one raised by Donald Turner with regard to non-algorithmic-enhanced oligopolistic coordination:[90] how should the remedy be structured? Should the algorithm be mandated to ignore its competitors' potential moves? Such a requirement may well undermine competition.[91] Therefore, the issue of remedy should be well thought through, before the law is changed.

So far we have focused on parallel conduct among different algorithmic consumers. We now turn to parallel conduct among different *users of the same algorithmic consumer*, which together might create anticompetitive effects. Once again, the question arises whether an "agreement" is created among such users, or between each user and the algorithm's designer or owner.[92]

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[88] Ezrachi & Stucke, *Artificial Intelligence*, *supra* note 6.

[89] See the famous debate between Turner and Posner: Donald F. Turner, *The Definition of Agreement Under the Sherman Act: Conscious Parallelism and Refusals to Deal*, 75 HARV. L. REV. 655, 671 (1962); Richard A. Posner, *Oligopoly and the Antitrust Laws: A Suggested Approach*, 21 STAN. L. REV. 1562 (1969).

[90] Turner, *ibid*.

[91] Ezrachi & Stucke, *Artificial Intelligence*, *supra* note 8.

[92] The question whether such conduct creates anti-competitive effects is a separate issue. In most instances the use of an exclusionary algorithm will create limited effects on competitive conditions in the market. Yet when used to make consumption decisions by a significant portion of demand (either due to the

One of the unique features of the digital world is the ability to create a group that can act in parallel for a joint cause on an ad hoc basis, without any formal organization. The negligible costs of communicating and processing information make coordination and integration cost-effective in a way that was not available before, enabling large-scale collaborations. As forcefully argued by Benkler, digital networks have facilitated a radically different mode of production where goods and services could be generated by a large number of peers who are not formally organized by firms, governments, or any hierarchical institutional structure.[93] Classic examples of such mass collaboration in producing creative works are Wikipedia and Free Software. Similarly, recent years have seen the flourishing of grassroots political action with no organizational or legal structures. The low costs of online coordination have facilitated a new, radically decentralized mode of ad hoc political action, by unorganized crowds: individuals and NGOs use the internet to raise awareness, disclose information, organize political pressure and engage in political action such as boycotts and protests.[94]

A similar type of conduct might arise with regard to users of algorithmic consumer systems. One possibility is users' intentional decision to use a single algorithm to bargain for their trade conditions. Should a sufficiently large number of users make a similar choice, the algorithmic consumer may integrate the purchasing decisions of a large number of consumers and enjoy

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cumulative effect of consumption decisions of many users through the algorithm or a consumption decision made by one significant user), the algorithm can erect entry or expansion barriers for those excluded by it, and significantly affect competition.

[93] YOCHAI BENKLER, THE WEALTH OF NETWORKS: HOW SOCIAL PRODUCTION TRANSFORMS MARKETS AND FREEDOM (2006). *See Also* CLAY SHIRKY, HERE COMES EVERYBODY: THE POWER OF ORGANIZING WITHOUT ORGANIZATIONS (2008); DON TAPSCOTT & ANTHONY D. WILLIAMS, WIKINOMICS: HOW MASS COLLABORATION CHANGES EVERYTHING (2006); JEFF HOWE, CROWDSOURCING: WHY THE POWER OF THE CROWD IS DRIVING THE FUTURE OF BUSINESS (2008).

[94] The Arab Spring, where repressive regimes were toppled by protesters organized via social media, is a classic example. This wave of online political activism did not skip Western democracies, were the Net was used to uncover knowledge (Wikileaks), to raise awareness (the campaign against SOPA/PIPA), and to coordinate street protests worldwide (from the 2099 Iranians election protest to the 2011 streets protest against ACTA in Europe).

significant market power. This can be used to engage in anticompetitive conduct. Consumers may then enjoy its fruits.

To determine whether an "agreement" exists, several scenarios should be distinguished. In the first, consumers agree among themselves to use the same algorithm. Clearly, a horizontal agreement exists. [95] Whether they engage in an anticompetitive agreement is a separate question, which is partly based on their awareness of the probable anticompetitive effects of their parallel use of the algorithm.[96] Indeed, the coordination of purchasing behavior might be based on benign considerations such as enabling the algorithm to potentially make better choices, based on crowd-smart and big data analysis. Furthermore, if the consumer is an end consumer he would generally not benefit from the exclusionary conduct by the algorithm, but only from exploitative conduct.

A more likely scenario arises when each user makes a unilateral decision to join the algorithm without a prior agreement, based on recommendations of other users or his own analysis of the comparative advantages of different algorithms. While each consumer enters into a direct vertical agreement with the algorithm's supplier, no horizontal agreement among consumers exists. The consumer might not be aware that the better trade terms were achieved due to the algorithm's market power, to which he contributed. This is a simple case. A more complicated one arises when the consumer is aware that the algorithm has significant market power, which he monopolizes to get better trade terms. It seems to us that as in the example above, while an "agreement" exists, the focus should be on the potential for anticompetitive harm.[97]

The fact that the *user is one-step-removed* from the decision, and hence perhaps even unaware of the relevant decision parameters set

[95] This is similar to the hub-and-spoke example analyzed by Ezrachi & Stucke, *Artificial Intelligence*, *supra* note 6, at 8.

[96] For a recent case raising these questions in the context of Uber see Opinion and Order, Meyer v. Kalanick [2016] S.D.N.Y. <https:// arstechnica.com/wp-content/uploads/2016/04/Untitled.pdf> (denying motion to dismiss). See also Salil K. Mehra , US v. Topkins: can price fixing be based on algorithms? 7(7) Journal of European Competition Law & Practice 470, 47 2016.

[97] The above analysis, while relating to algorithmic consumers, can also relate to algorithmic suppliers which may block the access to the market for some of the former

by the algorithm, also creates challenges regarding intent. For an anticompetitive agreement to arise, it is generally sufficient that the parties to the agreement be aware of the factual elements of the offense. When the agreement is regarded as per se illegal, an exception arises and no proof of intent is necessary.[98] For the purpose of the discussion below, let us assume that the algorithm purposely excludes or discriminates against a certain supplier for anticompetitive reasons. In such a situation, can we relate this anticompetitive intent to the user?

The answer is not simple. On the one hand, the user chose to use the algorithm and might have checked with the algorithm's supplier whether an anticompetitive result might arise. On the other hand, algorithms are generally black boxes for their users. Furthermore, once we demand that the user be made aware of the algorithm's decisional parameters, some of the benefits of using the algorithm in the first place (mind at rest, saving time, etc.) might be lost. Moreover, as elaborated above, users who are not competitors will generally not have any incentive to exclude either their suppliers or suppliers of other algorithmic consumers. Finally, even if the user is aware of the exclusionary node in the algorithm, he might not be aware of the cumulative market power of all those who use the algorithm, which creates the harm to competition. Such anticompetitive effect would depend on factors not necessarily under the individual user's control and which could change over time. We therefore suggest not assuming that the user is aware of the potential anticompetitive effect, unless this is the result of gross negligence.[99] However, where the user is aware of the exclusionary node and its

[98] *See, e.g.*, United States v. Gillen, 599 F.2d 541, 545 (3d Cir. 1979) ("in price-fixing conspiracies, where the conduct is illegal per se, no inquiry has to be made on the issue of intent beyond proof that one joined or formed the conspiracy"). For an interesting analysis of awareness in a computerized system *see* C-74/14 *Eturas and others*, (ECJ, 21.1.2016), ECLI:EU:C:2016:42.

[99] *See* Andreas Heinemann and Aleksandra Gebika, *Can Computers Form Cartels? About the Need for European Institutions to Revise the Concertation Doctrine in the Information Age*, JOURNAL OF EUROPEAN COMPETITION LAW & PRACTICE (2016)("If pricing is completely delegated to software...with the object or effect of harmonising prices between competitors (or to impose vertical price fixing), the 'Cartel of the Machines' amounts to a cartel between undertakings. In these cases, traditional meetings or forms of communication are replaced by an algorithm which renders direct concertation superfluous.").

potential anti-competitive effects, the fact that a sophisticated system containing an autonomous algorithm performed it should make no difference.[100]

Most of these considerations are not relevant to the designers or suppliers of such algorithms. Yet as discussed above, algorithmic consumers are often designed to perform in a way that might not be fully predictable by anyone but the designer. Accordingly, another challenge arises when the *algorithm uses deep learning* in its decision-tree, the process by which the algorithm teaches itself to better respond to market conditions from past actions. Then even the algorithm's designer might not be aware of its anticompetitive decision. In such situations intent could possibly be based on the supplier's awareness of the possibility of harm. To avoid liability the designer may need to code the algorithm to avoid anticompetitive conduct ("never exclude a specific supplier, even if it is in your economic interest to do so"). Furthermore, suppliers of algorithms may well be the "cheapest cost avoiders."[101] Yet to be socially welfare-enhancing, this solution must be technologically possible, and limiting the algorithm in such a manner should not carry a price (e.g., of recoding the algorithm) significantly higher than the benefits accruing to society from not applying such limitations (e.g., the algorithm's higher level of complication negates many of its benefits). Otherwise, the test should be based on the probable consequence of one's conduct.[102] For instance, if a supplier creates an algorithm to reduce costs, knowing that through self-learning this algorithm will find and choose a dominant strategy which is anticompetitive, intent may be established.[103]

An interesting issue relates to an exclusionary decision based on long-term considerations of competition. For instance, assume that an algorithmic consumer is designed to avoid buying any, or more than a certain portion of, products from a monopolistic firm, in order

[100] *See*, by way of analogy, Gabriel Hallevy, *Unmanned Vehicles – Subordination to Criminal Law under the Modern Concept of Criminal Liability*, 21 J.L. INFO. & SCI. 200, 202–05 (2012).
[101] GUIDO CALABRESI, THE COSTS OF ACCIDENTS: A LEGAL AND ECONOMIC ANALYSIS (1970).
[102] Hallevy, *supra* note 1004, at 206–08.
[103] Ezrachi & Stucke, *Artificial Intelligence*, *supra* note 6, at 27.

to allow new competition to grow in the market. Furthermore, such considerations can go beyond the specific market, attempting to level the playing field in other, related, markets (such as the market for mega platforms). We suggest that such considerations be accepted as valid justifications in the right circumstances, that is, whenever there is a strong probability that the algorithm's decision-tree will indeed further competition and welfare in the long run. The exclusion however must be proportional to the harm to certain market players and necessary to achieve the pro-competitive goal.

Finally, an interesting aspect that might burden enforcement efforts is the weight to be given to different decision parameters. If a certain algorithmic consumer gives little weight to a certain parameter, thereby indirectly excluding a certain supplier, how will it be determined whether this constitutes anticompetitive conduct? The allegations against Google may provide a glimpse of what could be expected in such cases. Google claimed that the weight given in its search algorithm to different parameters is protected under the First Amendment of the Constitution as free speech.[104] This raises the provocative question should we not expect such arguments also regarding our algorithmic consumer's choices for a detergent for our washing machine or for pet food?

As we have shown, while antitrust is generally sufficiently flexible to apply to solve the third challenge raised by algorithmic consumers, it is much more limited in its ability to deal with the first two challenges. Other regulatory tools might thus need to be devised, given that currently antitrust is the main tool in the regulatory toolbox to deal with such issues.

CONCLUSIONS

We are standing on the verge of a brand new world as to how we buy and sell. Roles that for centuries have been performed by humans will soon be transferred to algorithms. This change is inevitable, given technological developments that give algorithmic

[104] *See, e.g.,* Search King, Inc. v. Google Technology, Inc. No. Civ-02-1457-M (W.D. Okla., Jan. 13, 2003).

consumers strong comparative advantages over human consumers in some decision-making processes. These trends are intensified by the rise of the Internet of Things (IoT).

It is thus essential that we recognize the effects of such a change on market dynamics: how the systematic deviation of consumer purchase decisions from the assumptions of the past—whether with regard to influences on human decision-making, its limitations and advantages—change competition and welfare. This was the first goal of this article. As elaborated, algorithmic consumers change fundamental factors, including consumer choice, market demand, product design, and marketing techniques. They affect not only consumers but also suppliers. They have the potential to significantly increase competition, and at the same time to significantly limit it.

Our second goal was to identify and analyze some of the regulatory challenges that arise from these changes, and in particular the ability of existing regulatory tools to ensure that consumers enjoy the benefits algorithmic consumers have in store. As has been shown, algorithmic consumers challenge the application of some of our regulatory tools, which were designed to cater to human transactions. When computer code determines important transactions, some of the assumptions on which current regulation is based must be changed. In particular, we explored how the antitrust notions of agreement and intent have to be rethought to ensure that competition is indeed protected.

We also pointed out some market failures and regulatory challenges which may require the creation of additional regulatory tools. One such regulatory challenge is the potentially significant increase in buyer power, which does not result from or lead to exclusionary conduct. The social welfare effects of the exploitation of such power, which generally do not come under antitrust, should be carefully analyzed.

Finally, competition among suppliers of algorithms will not necessarily positively affect all factors that influence social welfare. For example, applying cyber-security measures to protect algorithms from cyber-attacks at a socially optimal level is costly. One would expect competition to exclude unsecured systems by increasing demand for safer applications. Yet consumers often lack the information and skills necessary to assess cyber-risk. Moreover, security failures create externalities, by increasing vulnerabilities in other networks and products, which each supplier of algorithms does not take into account. Consequently, suppliers of algorithms will most probably not create protections at the socially optimal level.[105] Other forms of regulation might then be necessary to complement antitrust.

[105] Chris Johnson, The Role of Cyber-Insurance, Market Forces, Tort and Regulation in the Cyber-Security of Safety-Critical Industries, Paper presented at the 10th IET System Safety and Cyber Security Conference, (Oct. 21, 2015).